Towards Sustainable Freight Energy Management

Development of a Strategic Decision Support Tool

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Declaration

I, Tanya Elizabeth Lane, hereby declare that the work on which this thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university. I authorise the University to reproduce for the purpose of research either the whole or any portion of the contents in any manner whatsoever.

Signature: Signed by candidate   Date: 17/10/2019

This dissertation is dedicated to the memory of my beloved father, Professor Ian Ernest Lane, the inspiration for my academic pursuits.

Preface

"It always seems impossible until it is done."

Nelson Mandela

The road to completion of this dissertation has been long, but ultimately very rewarding. Not only did it lead to personal growth and development of my academic ability, meaningful professional relationships were initiated and strengthened throughout the process, as well.

I would like to express my sincere gratitude to all students and staff members at the University of Cape Town, Stellenbosch University and the University of Pretoria, who, in some or other way, contributed to the successful completion of this research. In particular, I would like to single out Professor Marianne Vanderschuren, my research supervisor and mentor. Thank you for your continued faith in me, your endurance, your valuable inputs and for always making our collaborations a pleasant experience. I look forward to our future endeavours.

Cheryl Wright deserves a special thank you for her proofreading and editing assistance and I want to thank the Department of Transport for their financial support during the early stages of this research.

Lastly, I need to thank my wonderfully supportive family. To my father, Ian – you inspired my academic career and demonstrated how to live life loving what you do. To my mother, Annette – you have always been my cheerleader. Thank you for both the emotional and physical support throughout this journey. To Emile, my husband – you deserve a special thank you. Your unwavering confidence in me, your patience, motivation, support and love has been fundamental to my completion of this childhood ambition. Finally, to my daughter, Carmen – thank you for motivating me to conclude this chapter in my life and inspiring me to be better.

I am proud of the work presented in this dissertation and even more proud that it has, finally, been completed.

Tanya Lane-Visser

Cape Town, May 2019

Abstract

Freight transportation, in its current shape and form, is on a highly unsustainable trajectory. Global demand for freight is ever increasing, while this demand is predominantly serviced by inefficient, fossil fuel dependent transportation options. The management of energy use in freight transportation has been identified as a significant opportunity to improve the sustainability of the freight sector. Given the vast amount of energy mitigation measures and policies to choose from to attempt this, decision-makers need support and guidance in terms of selecting which policies to adopt – they are faced with a complex and demanding problem.

These complexities result, in part, from the vast range, scope and extent of measures to be considered by decision-makers. The tool developed needs to encompass a suitable methodology for comparing proverbial apples to oranges in a fair and unbiased manner, despite the development of one consistent assessment metric that can accommodate this level of diversity being problematic. Further to this, decision-makers need insight into the extent of implementation that is required for each measure. Because the level of implementation of each measure is variable and the extent to which each adopted measure will be implemented in the network needs to be specified, the number of potential measure implementation combinations that decision-makers need to consider is infinite, adding further complexity to the problem.

Freight energy management measures cannot, and should not, be evaluated in isolation. The knock-on effects of measure adoption on the performance of other measures need to be considered. Measures are not all independent and decision-makers need to take these dependencies and their ramifications into account. In addition, there is dimensionality to be accounted for in terms of each measure, because one measure can be applied in a variable manner across different components of the freight network. A unique and independent decision needs to be made on the application of a measure for each of these network components (for example for each mode).

Decisions on freight transportation impact all three traditional pillars of sustainability: social, environmental and economic. Measure impacts, thus, need to be assessed over multiple criteria. Decisions will affect a variety of stakeholders and outcomes must be acceptable to a range of interested parties. Sustainability criteria are often in conflict with one another, implying that there are trade-offs to be negotiated by the decision-makers. Decision-makers, thus, need to propose system alterations, or a portfolio of system alterations, that achieve improvements in some sustainability respects, whilst maintaining a balance between all other sustainability aspects. Moreover, the

magnitude of impacts (be it positive or negative) of a measure on the sustainability criteria is variable, adding additional dimensionality to the problem.

The aim of the research presented in this dissertation was to develop a decision support tool which addresses the complexities involved in the formulation of freight transport energy management strategies on behalf of the decision-makers, facilitating the development of holistic, sustainable and comprehensive freight management policy by government level decision-makers. The Freight Transport Energy Management Tool (FTEMT) was developed in response to this research objective, using a standardised operations research approach as a roadmap for its development.

Following a standardised operations research approach to model development provides a structure where stakeholder participation can be encouraged at all the key stages in the decision-making process; it offers a logical basis for proposing solutions and for assessing any proposed suggestions by others; it ensures that the appraisal of alternative solutions is conducted in a logical, consistent and comprehensive manner against the full set of objectives; and it provides a means for assessing whether the implemented instruments have performed as predicted, enabling the improvement of the model being developed.

The FTEMT can be classified as a simulation optimisation model, which is a combination between multi-objective optimisation and simulation. The simulation component provides a suitably accurate representation of the freight system and affords the ability to approximate the effect that measure implementation will have on the sustainability objectives, whilst the optimisation component provides the ability to effectively explore the decision space and reduces the number of alternative options (and, therefore, the complexity) that decision-makers need to consider. It is this simulation optimisation backbone of the FTEMT that enables the tool to address all the complexities surrounding the problem, enabling the decision support produced by the FTEMT to provide the information necessary for decision-makers to steer the freight transport sector towards true sustainability.

Although this problem originates from the domain of sustainable transportation planning, the combination of operations research and transport modelling knowledge applied proved essential in developing a decision support tool that is able to generate adequate decision support on the problem.

To demonstrate the use and usefulness of the decision support system developed, a fictitious case study version of the FTEMT was modelled and is discussed throughout this dissertation. Results from the case study implementation were used to verify and validate the tool, to demonstrate the decision support generated and to illustrate how this decision support can be interpreted and incorporated into a decision-making process. Outputs from the case study FTEMT proved the tool to be operationally valid, as it successfully achieved its stated objectives (the FTEMT unearths a Pareto set of solutions close to the true efficient frontier through the exploration of different energy management measure combinations).

Explained in short, the value of using the FTEMT to generate decision support is that it explores the decision space and reduces the number of decision alternatives that decision-makers need to consider to a manageable number of solutions, all of which represent harmonic measure combinations geared toward optimal performance in terms of the entire spectrum of the problem objectives. These solutions are developed taking all the complexity issues surrounding the problem into account. Decision-makers can, thus, have confidence that the acceptance of any one of the solutions proposed by the FTEMT will be a responsible and sound decision. As an additional benefit, preferences and strategic priorities of the decision-makers can be factored in when selecting a preferred decision alternative for implementation. Decision-makers must debate the trade-offs between solutions and need to determine what they are willing to sacrifice to realise what gain, but they are afforded the opportunity to select solutions that show the greatest alignment with their official mandates.

The structure of the FTEMT developed and described in this dissertation presents a practical methodology for producing decision support on the development of sound freight energy management policy. This work serves as a basis to stimulate further scholarship and expands upon the collective knowledge on the topic, by proposing an approach that is able to address the full scale of complexities involved in the production of such decision support.

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List of Acronyms

ACN	Aircraft classification number
AMOSA	Archived multi-objective simulated annealing
CO_2	Carbon dioxide
ESAL	Equivalent single axle load
FTEMT	Freight transport energy management tool
GHG	Greenhouse gas
GIS	Geographical information systems
GM*X*	Government level freight energy management measure *x* considered for inclusion in the case study
ICE	Internal combustion engine
LM*X*	Logistics sector level operational instrument *x* considered for inclusion in the case study
MCDM	Multi-criteria decision-making
MJ	Megajoule
MOO	Multi-objective optimisation
OD pair	Origin-destination pair
PCN	Pavement classification number
Tkm	Tonne-kilometres
Wh	Watt-hours

1 Introduction

1.1 Background

Although the debate about the need for sustainable development has been around for many years, the worldwide increased occurrence of extreme weather events, as a consequence of global warming and the associated devastation caused, is underscoring the importance of this matter, yet again. The United Nations' (UN) Paris Agreement entered into force on 4 November 2016, with a central aim to strengthen the global response to the threat of climate change by keeping a global temperature rise this century well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5°C (UNFCCC, 2018). The Paris Agreement required all Parties to put forward their best efforts through nationally determined contributions (NDCs) – pledges to reduce greenhouse gas (GHG) emissions by a certain margin, by each country. Diffenbaugh *et al.* (2018) found that the actual pledged national commitments are expected to only curtail global warming to 2°C or 3°C and, thus, not meet the UN's proposed targets. They found that this level of warming is likely to lead to substantial and widespread increases in the probability of historically unprecedented extreme hot, wet and dry weather events. Should the UN target of 1°C to 2°C be achieved, these probability increases will be substantially limited, however, many areas are still likely to experience significant increases in the probability of unprecedented events. It is imperative that governments prioritise this matter in all their endeavours and decisions.

The transportation sector is one of the greatest sources of GHG emissions globally and has increased its emissions at the fastest rate of all energy end-use sectors since 1970 (Sims *et al.*, 2014). Figure 1.1 shows that direct emissions from the transport sector rose 250% between 1970 and 2010, with road transportation being the main contributor. Transportation accounted for 28.8% of global total final energy consumption in 2015 (IEA, 2017a). Transport was the sector with the largest end-use energy demand, at 35% of total end-use energy demand in 2014, measured in the 19 International Energy Agency (IEA) countries for which data are available for most end-uses[1] (IEA, 2017a). In total, 40% of this transport end-use energy demand was freight related. Chapter two further elaborates on the relationship between transport, energy and sustainability.

[1] Australia, Austria, Canada, Czech Republic, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, New Zealand, the Netherlands, Spain, Sweden, Switzerland, the United Kingdom and the United States

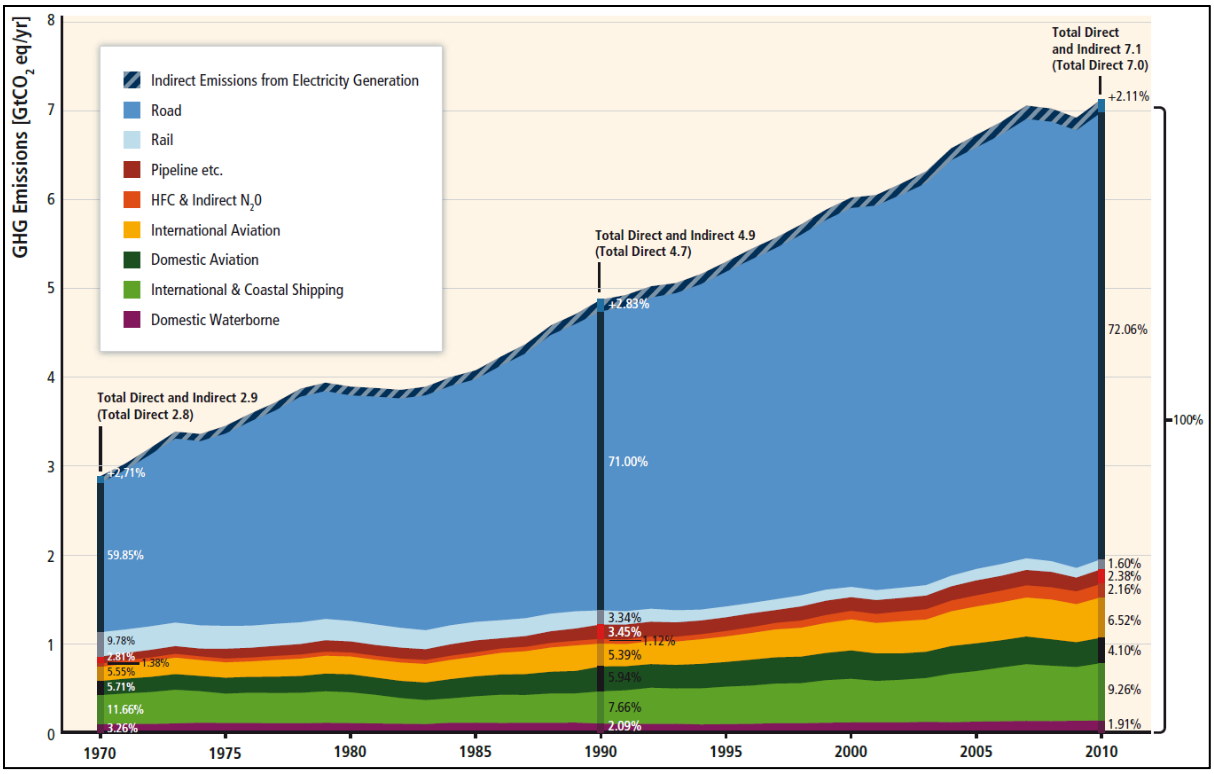


Figure 1.1 Historic GHG emissions of the transport sector by mode (Sims et al., 2014)

Time series analyses and projections in the literature all indicate that the transport sector is continuing to grow in terms of energy demand, making it an important research area for global emissions reduction and sustainability improvement. Without aggressive and sustained mitigation policies being implemented, transport emissions could nearly double (reaching around 12 Gt CO_2eq/year) by 2050 (Sims *et al.*, 2014).

Considerable amounts of research have gone into (and are still ongoing) proposing, developing and analysing transport energy demand and emissions mitigation policies. In 2011, the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) published their “Avoid-Shift-Improve (A-S-I)” approach to sustainable mobility (GIZ, 2011). The approach seeks to achieve significant GHG emission reductions, reduce energy consumption, to promote alternative mobility solutions and to develop sustainable transport systems. The A-S-I approach (summarised in Figure 1.2) is a three-pronged approach. “Avoid” refers to integrated land-use planning and other transport demand management policies that reduces or avoids the need to travel. “Shift” policies and instruments seek to improve trip energy efficiency for trips that cannot be avoided, by shifting the trips towards more energy efficient transport modes (such as non-motorised transport or public transport). If a trip cannot be avoided, nor shifted to a different mode of transport, the energy efficiency of the trip can still be “Improved” when vehicle, fuel and operational efficiency is optimised. Essentially, the A-S-I approach improves upon the transport demand, mode choice and technology deployment within a network.

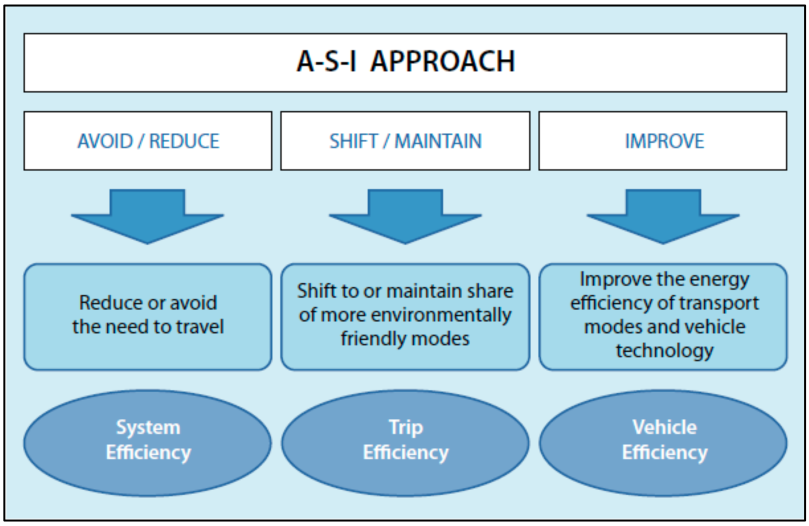
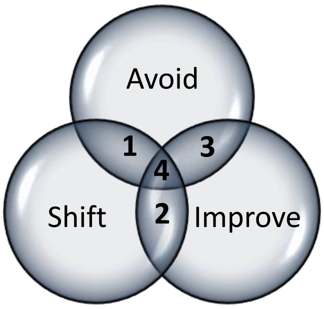


Figure 1.2 The Avoid-Shift-Improve approach to sustainable mobility (GIZ, 2011)

Figure 1.3 displays a categorisation of transport energy mitigation measures according to the A-S-I approach, as listed in Lane and Vanderschuren (2010a). Cazzola and Teter (2016) provides another source of information on mitigation measures categorised according to the A-S-I approach. An alternative approach to categorising measures is to group them according to the nature and function of the measure. Dalkmann *et al.* (2011) proposed the following five measure categories: policy measures, institutional and governance measures, infrastructure measures, operational measures and technology and research and development (R&D) measures. The complete list of measures explored in their report is provided in Appendix A. Lane and Vanderschuren (2010a), in turn, defined seven distinct measure categories as follows:

- Planning instruments include measures on land use and infrastructure, encompassing public transport and non-motorised modes, as well as new low carbon technologies and fuels.
- Regulatory instruments include norms, rules or standards to limit the behaviour of individual actors and corporate entities, defining allowable levels of emissions, types of vehicle design and technologies, vehicle emissions standards, fuel standards and amount of travel activity.
- Economic instruments use cost-based incentives (taxes, fees, rebates and markets) to discourage high carbon transport and make low carbon options more attractive.
- Instruments that provide information in easily accessible formats to educate the public and increase the awareness of alternative modes, leading to a modal shift towards public transport, walking or cycling, for example, or towards improved driver behaviour and reduced fuel consumption, are called educational instruments.
- Technological instruments reduce the impact on carbon emissions when travel by motorised transport is necessary, for example, through cleaner or alternative fuels and improving vehicle efficiency.

- Management instruments aim to achieve greater operational efficiency in transport (such as Intelligent Transport Systems). These instruments often merely require the training of human resources to unlock the potential benefits embedded in the system.
- Travel replacement instruments (travel demand management) that negate the need for travel through technology or spatial planning.



AVOID	1	SHIFT	2	IMPROVE	3
Land Use Planning	Urban Infrastructure (Re) Design	Infrastructure Development for New Propulsion Systems	Taxes and Charges	Fuel Quality Standards	Traffic Management
Vehicle Occupancy Management		Provision of Integrated Public Transport Systems	Rebates	Vehicle Emissions Standards	Fleet Management
Vehicle Load Management		Inter-modal Infrastructure Development	Subsidies	Training of Transport Operators	
Information Technology Substituting Travel		Infrastructure Provision for New Energy Sources	Green Transport Marketing Campaigns	Training of Human Resources for Traffic Management	
Logistics Management		Incentives for New Technology Adoption	Infrastructure Maintenance	Vehicle Maintenance	
		Equitable Infrastructure Development for All Modes	Intelligent Transport Systems	Vehicle Design Improvements	

Figure 1.3 Sustainable mobility mitigation measures classified according to the A-S-I approach (Lane and Vanderschuren, 2010a)

For each of these measures and measure categories, a plethora of transport energy mitigation approaches has been researched and proposed, with many still under development. In a recent publication by the IEA, *The Future of Trucks* (IEA, 2017b), freight specific energy mitigation measures are listed and discussed. There is a discussion on policy frameworks affecting road freight fuel intensity, including policy measures that address market barriers to truck fuel economy investments, vehicle efficiency regulations, pricing policies to improve the energy efficiency of trucking, Green

Freight Alliances and scrappage schemes. Furthermore, opportunities and barriers for reducing road freight energy demand and emissions growth are divided into three main mechanisms (IEA, 2017b):

- systemic improvements, i.e. improvements to the way the larger road freight system operates with a focus on reducing the road activity (in tonne-kilometres (tkm)) required to deliver the same amount of goods,
- improving vehicle efficiency, i.e. reducing the amount of energy used by individual trucks,
- the use of alternative fuels, i.e. a switch away from the use of oil-based transport fuels to other fuels, such as natural gas, biofuels, electricity or hydrogen.

Table 1.1 and Table 1.2 summarises the systems improvements discussed. Similarly, Table 1.3 lists the near-term energy efficiency measures analysed in *The Future of Trucks* (IEA, 2017b). Hybridisation is mentioned as an efficiency improvement technology with longer payback periods. The alternative fuels and powertrains analysed in the document are: natural gas, biofuels, electric trucks and hydrogen. The report provides a very good literary reference for more detailed information on freight energy mitigation measures.

In Sims *et al.* (2014) energy intensity reduction technology options for heavy duty vehicles (HDVs), ships, trains and aircraft, as well as fuel carbon intensity reduction options related to the use of natural gas, electricity, hydrogen and biofuels, are discussed. Technology-related behavioural aspects concerning the uptake and use of new technologies, behaviour of firms and rebound effects are also addressed. Finally, a discussion on infrastructure, urban form and modal shift options, for both passenger and freight transport, is provided. A summary table of the freight related mitigation options, included in Sims *et al.* (2014), is provided in Appendix A.

Despite all the research on the topic, numerous gaps in knowledge and data remain, complicating the assessment of mitigation potential in the transport sector. "There is a lack of comprehensive and consistent assessments of the worldwide potential for GHG emission reduction and especially costs of mitigation from the transport sector. Within this context, the potential reduction is much less certain for freight than for passenger modes" (Sims *et al.*, 2014).

Sims *et al.* (2014) state that gaps are evident in the basic statistics on the costs and energy consumption of freight transport, especially in developing countries. They also note that data and understanding relating to freight logistical systems and their economic implications are poor, as are the future effects on world trade of decarbonisation and climate change impacts – making it difficult to design new low-carbon freight policies.

Table 1.1 Measures to improve systems efficiency in road freight with low implementation barriers (IEA, 2017b)

Category	Enablers	Barriers	Potential energy saving	Examples / Notes
Use of high-capacity vehicles (HCVs)	Performance-based standards Intelligent Access Program as in Australia	Concerns about safety and road infrastructure impacts; potential for 'reverse' mode shift (away from freight rail); increased demand for just-in-time delivery	Direct savings may be upwards of 20%, but actual savings may be lower, depending on the extent of activity rebound and of modal shift from rail.	Regulations allow for the operation of HCVs at the national or regional level in Australia, Brazil, Canada, Finland, Mexico, South Africa and Sweden.
Route optimisation	Geographic information system real-time routing data Relaxing delivery time constraints	Increased demand for just-in-time delivery	From 5%-10% for intra-city trucking, but closer to only 1% for long-haul missions.	UPS ORION, which in 2017 began its global rollout.
Platooning*	Vehicle communication and automation technologies	Traffic congestion, and mixed traffic; road capacity limitations. Need to ensure safety	From 5% to 15% for a three-truck platoon traveling at 80 km/h (depending on gap distance).**	Japan's "Energy ITS" (2008); the California PATH programme (2011); the European Commission's SARTRE project (2017).
Driver training and feedback	Rewards programmes in mid- to large fleets	Lack of consolidation among carriers (many small owner-operators)	Immediate savings of between 3% and 9% (the latter in long-haul operations).	FleetSmart, Canada, as well as many examples among Finnish, German, US and other carriers.
Improved vehicle utilisation (including backhauling)	Better data collection (as enabled by ICT) Collaboration and on-line exchanges alliances among carriers and logistics service providers (LSPs)	Legal frameworks that restrict anti-competitive behaviour (and thereby impede co-ordination among carriers, shippers, and LSPs). Lack of industry consolidation among carriers.	Potentially substantial, but difficult to quantify. Savings are enabled by better tracking basic freight operational parameters and adopting industry best practices in logistics.	The European Union's CO3 Project on horizontal supply chain collaboration. Online freight exchanges co-ordinate a large fraction of road freight movements in the United States and the United Kingdom.
Last-mile efficiency measures	Prediction of dynamic demand Increased competition, including market entry of LSPs	Increased demand for just-in-time delivery Urban traffic congestion	Likely in the range of 1-5%.	Delivery service plans developed by Transport for London; Binnenstadt service in 11 towns in the Netherlands.
Re-timing urban deliveries	Incentives to shipment receivers to accept the insurance and logistical impacts of shifting to early morning and off-hour deliveries	Concerns from local citizens about noise Customer concerns with product quality and condition upon delivery Constraints imposed by just-in-time delivery	Very difficult to estimate and generalise. Across the urban truck fleet as a whole, fuel- and GHG emission reductions are estimated in the range of 10%-15%.	A complete shift to off-hour deliveries led to a reduction in local pollutants in the range of 45-67% in New York, Bogotá and São Paulo. Pilots include POLIS (European Union) and PIEK (the Netherlands).
Urban consolidation centres (UCCs)	City regulatory policies to reduce congestion and promote air quality	Design is highly city-specific, making dissemination of best practices difficult Fiscal sustainability challenges in the absence of a dedicated public funding stream or viable business model	Vehicle activity, fuel use and CO_2 emissions within urban centres can be reduced by 20-50%.	UCCs group shipments from multiple shippers and consolidate these onto a single truck for delivery to a given geographic region. Various global cities, most of which are located in Europe, and Japan.

* Platooning refers to the practice of driving heavy-duty trucks (primarily tractor-trailers or rigid trucks) in a single line with small gaps between them to reduce drag and thereby save fuel during highway operations. Vehicle-to-vehicle and vehicle-to-infrastructure (V2V and V2I) communication technologies can enable trucks to drive in very close proximity without sacrificing safety or manoeuverability.

** According to Tsugawa, Jeschke and Shladovers (2016), the average fuel saving for three trucks driving at 80 km/hr with a 10-m gap is about 8%, and 15% with a 4-m gap. High levels of vehicle autonomy would be needed to safely operate trucks with a 4-m gap.

Sources: Browne, Allen and Leonardi (2011); Wiki4City (2014); Holguín-Veras (2016); McKinnon (2016b); Wallenburg and Raue (2011).

Table 1.2 Measures to improve systems efficiency in road freight with high implementation barriers (IEA, 2017b)

Category	Enablers	Barriers	Potential energy savings	Examples/Notes
Physical Internet	Legal and regulatory frameworks; ICT to collect, process and protect proprietary data	Anti-trust or other non-harmonised national legislative frameworks	Work to date on this concept suggests a potential 20% systems-wide efficiency improvement.	An open, shared system of all physical resources (e.g. ports and warehouses) used in goods delivery. The realisation of complete collaboration across shippers and carriers to maximise vehicle utilisation (Wible, Mervis and Wigginton, 2014).
Co-loading*	Legal and regulatory frameworks to promote energy savings while protecting companies' intellectual property	Just-in-time delivery; lack of industry consolidation among shippers and carriers	Estimated at 5-10%.	Co-loading uses supply chain collaboration within a company and/or across firms to increase vehicle utilisation (load) on outbound operations (Van Lier et al., 2010).
Crowdshipping/ Co-modality/Digital freight matching**	Deregulation of urban delivery markets as well as the protection of citizen-carriers' labour and liability	Legal and regulatory hurdles surrounding liability and insurance Requires a certain scale to realise savings	Difficult to assess; highly dependent on the degree of spatial and temporal matching. Likely 5-10% in urban areas, with the possibility of counterproductive impacts.	**Crowdshipping**: a recent proliferation of platforms and apps in Australia, the People's Republic of China (hereafter, "China"), the United States and throughout the European Union. **Co-modality**: examples of using public transport infrastructure to ship goods exist in a few European and East Asian cities. **Digital freight matching (DFM)**: a proliferation of start-ups, concentrated in the United States, have entered the DFM market in the past five years.
Autonomous trucks	Clear and standardised regulations on technology certification, liability, security and privacy	Truckers' unions; hasty rollout could result in a single accident leading to public backlash	Limited and estimated to be 5% from smoother driving in other conditions. Potential rebound effects might be very substantial.	Rio Tinto's autonomous mining trucks in Australia (Rio Tinto, 2014). Otto's autonomous highway beer delivery (Isaac, 2016).

* Co-loading is discussed in the previous section as it is among the measures that can be taken to improve vehicle utilisation.

** Crowdshipping is when citizens perform the services of couriers. Co-modality refers to the usage of (often public) passenger transport modes for freight delivery. Digital freight matching is the use of online platforms and apps to match vehicles and cargo in real time. All three are described in more detail below.

Historically, high oil prices have stimulated improvements in freight energy efficiency, diversification of supply solutions and policies to affect demand - all supported by new, innovative technologies (Commission of the European Communities, 2006). Hart (1997) mentions that: "bottom-up pollution-prevention programmes have saved companies billions of dollars". To date, the business logic for greening of freight transport has been largely operational or technical and efforts have been driven by the freight transporters themselves (i.e. bottom-up). The high cost of fossil fuels and the need to reduce strategic dependency on them, should sustain an improvement in the potential of each mode of transport going forward, but perhaps not at the required pace.

Table 1.3 Near-term vehicle efficiency measures with a net savings over the vehicle lifetime (IEA, 2017b)

Measure	Description	Potential energy savings
Aerodynamics	A wide range of aerodynamic fittings (such as aft box tapers, aerodynamic tractor bodies, mud flaps, trailer tails, box skirts and cab/box gap fairings) can reduce the drag coefficient, thereby reducing road load.	Individual vehicle components reduce fuel use by 0.5-3%, depending on the truck type and aerodynamic retrofit.
Low rolling resistance (LRR) tyres; **Tyre pressure systems (TPS)**	LRR tyres can be designed with various specifications, including dual tyres or wide-base single tyres with aluminium wheels, and next-generation variants of these designs.	The potential ranges from about 0.5% to 12% in the tractor-trailer market. TPS alone could reduce fuel use by 0.5-2%.
Light-weighting	Broadly, all HDV vehicle types except utility trucks could cost-effectively reduce weight by upwards of 7% within the next ten years.	The CO_2 savings potential is about 1% by 2020, 2-3% by 2030 and 2.7-5% by 2050.
Transmission and drivetrain	Moving from manual to automatic/automated manual transmission can greatly improve efficiency. Adding gears, reducing transmission friction and using shift optimisation in manual automated or fully automated transmissions can also improve drivetrain efficiency.	Automatic/automated transmissions reduce fuel consumption by 1-8%, depending on truck type; other improvements lead to fuel savings of about 0.5-2.5%.
Engine efficiency	Engine improvements include increasing injection and cylinder pressures, both of which typically improve incrementally on a yearly basis.	Improvements in the coming decade could lead to fuel savings of approximately 4% (in service/delivery vehicles) to 18% (in long-haul trucks).
Idling reducing technologies	These include auxiliary power units and generator sets, battery air conditioning systems, plug-in parking spots at truck stops and thermal storage systems.	As much as 2.5% of the fuel consumed by road trucks may be due to idling operations. As such, this is an upper threshold on the potential fuel savings (energy savings are less).
Hybridisation	Parallel hydraulic hybridisation may be the most cost-effective near-term technology option for municipal utility vehicles, while electric hybridisation tends to be the best hybridisation option for most other mission profiles.	Dual-mode hybrid: 8-30% Parallel hydraulic hybrid: 15-25% Parallel hybrid: 6-35% – all ranges depend on vehicle type; gains are lowest (around 6%) on long-haul vehicles operating at constant highway speeds.

Note: The potential energy savings cited are for near-term (i.e. over the coming decade) technologies and measures that reduce the total cost of ownership over the vehicle or measure lifetime.

Sources: Aerodynamics: Schroten, Warringa and Bles (2012); US EPA/NHTSA (2016). Low-rolling resistance tyres and tyre pressure management systems: Schroten, Warringa and Bles (2012); Meszler, Lutsey and Delgado (2015); US EPA/NHTSA (2016). Light-weighting: Ricardo-AEA (2015). Transmission and drivetrain: Schroten, Warringa and Bles (2012). Engine efficiency: Schroten, Warringa and Bles (2012). Hybridisation: Law, Jackson and Michael (2011); Schroten, Warringa and Bles (2012). Idling reducing technologies: Vernon and Meier (2012); ANL (2013).

In spite of these bottom-up initiatives, however, there is broad agreement that present trends in transport are not sustainable and many conclude that fundamental changes in the technology, design, operation and financing of transport systems are needed (Greene and Wegener, 1997). As demonstrated in the World Energy Outlook (IEA, 2013a), strong policies are needed to induce necessary changes in the transport system and to steer development towards sustainability (Bongardt *et al.*, 2013). It appears that top-down approaches will also be required to facilitate a change of the required magnitude. “Business initiatives to decarbonise freight transport have begun but need support from policies that encourage shifting to low-carbon modes, such as rail or waterborne options where feasible, and improving logistics” (Sims *et al.*, 2014).

In almost all countries, comprehensive policy action can realise a huge potential to reduce emissions and generate various co-benefits. Figure 1.4 suggests that there is large untapped potential in reducing (especially) freight transport energy demand, considering that transport is the largest energy use sector. Governments and the freight industry both recognise a need for solutions to meet future challenges of GHG emissions reductions (Frey and Kuo, 2007). In fact, decision-makers all over the world are facing the challenge of developing sustainable (freight) transport systems.

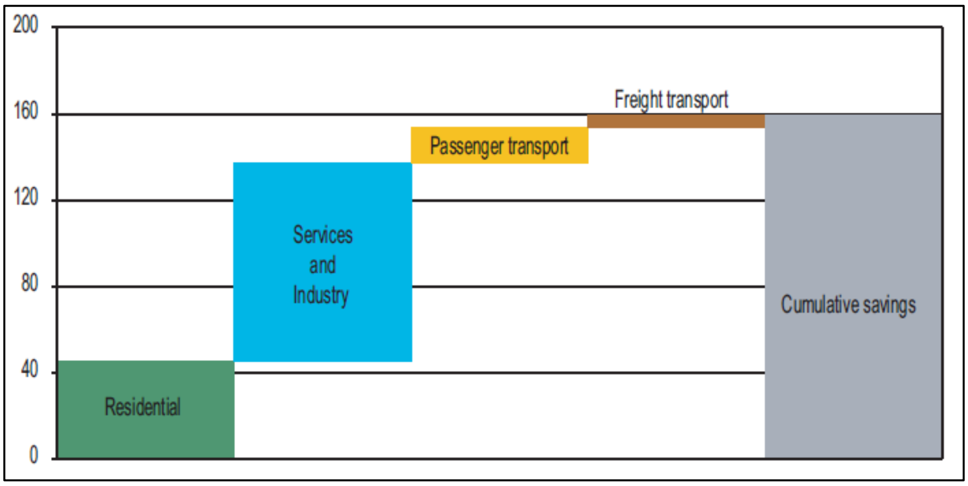


Figure 1.4 Estimated cumulative energy savings (expressed in exajoules) by sector in IEA between 2000 and 2015 (IEA, 2017a)

1.2 Problem Statement

Decision-makers are tasked with developing national policy that must steer the transport sector in a sustainable direction, but what does that policy look like? Given the vast amount of energy mitigation measures and policies to choose from, decision-makers need support in terms of selecting the policies to adopt. Determining which measures to implement as part of a comprehensive freight energy mitigation strategy and to what extent they should be implemented, is a complex problem (OECD, 2002). As May *et al.* (2005) explains: "The range of policy instruments and of ways in which they can be combined makes it particularly difficult to decide what the best strategy is." There is no silver bullet strategy or one-size-fits-all solution (Bongardt *et al.*, 2013) and an understanding of how best to design such integrated approaches is needed (May *et al.*, 2005).

The problem addressed in this dissertation is how to manage and address the complexity involved in the development of a freight energy mitigation strategy. As will be demonstrated in the following discussion, there are too many complicating factors (e.g. too many measure options, too many consequences, too many interactions between measures) to consider for this problem to have a simple answer.

The first level of complexity to deal with, is the vast range, scope and extent of measures to be considered by a decision-maker. How does one consider all the potential measures and, with new measures being developed daily, how does one, in the future, incorporate or accommodate new measures that cannot even be fathomed now? What complicates matters further, is the fact that measures are so heterogeneous in terms of their scope of application, impact and level of implementation – measures are inherently very different and diverse. As seen in the discussion on measures in Section 1.1, there are many different types of measures and different measures are needed for different transport modes. The problem with this is how one ensures that you are comparing apples with apples. Another complicating factor is to develop one consistent assessment metric that can accommodate this level of diversity. Sims *et al.* (2014) emphasise the need for assessments to be consistent and comprehensive.

Furthermore, the impact of a measure is not necessarily uniform – the extent of implementation and adoption of the measure makes a difference in terms of the overall impacts realised. A measure's effectiveness can also be affected by the specific location and context in which it is applied. Decision-making in the transport sector needs to be adapted to suit geographical circumstances and local political constellations, accommodating various conceptual ideas and competing visions in the process (Bongardt *et al.*, 2013). Decision-makers not only need insight into which measures to adopt, but also the extent of implementation that is required for each measure.

Freight transport is a system, implying that measures are related to one another. For example: alternative propulsion systems go hand-in-hand with alternative fuels, the infrastructure needed for these fuels and the acceptance of vehicles with alternative propulsion by the public (Dalkmann *et al.*, 2011). Elements and decisions made within the freight sector interact. Consequently, measures cannot, and should not, be evaluated in isolation. The knock-on (rebound) effects of measure implementation needs to be considered (Sims *et al.*, 2014), as well as the interaction between measures – certain decisions will limit others and certain decisions might mitigate (or boost) the impacts of others.

May *et al.* (2005) suggests that the best solution will likely be a combination (package) of mitigation measures. They explain that integration at the strategic level can potentially achieve benefits, both by using instruments which reinforce one another and by overcoming the barriers to implementation. It is often difficult for a single instrument to overcome a barrier, but a careful choice of combinations of instruments can reduce both financial and political barriers (May *et al.*, 2005). Whilst an individual instrument can have adverse impacts on certain groups of users, a careful choice of other instruments can help compensate the losers. A package of instruments is, thus, likely to be more effective than selecting any one instrument on its own. In this way, synergy, or complementarity, can be achieved between instruments; making the overall benefits greater than, or at least equal to, the sum of the parts. “The identification of instruments which might achieve such synergy or complementarity is at the core of successful transport planning” (May *et al.*, 2005). Because the level of implementation of each measure is variable and the extent to which each measure adopted is implemented needs to be specified, the number of potential measure combinations to explore is infinite, adding further complexity in developing adequate decision support.

The freight sector impacts all three traditional pillars of sustainability: social, environment and economic. Measure impacts, thus, need to be assessed over multiple criteria, as decisions will affect a variety of stakeholders and outcomes must be acceptable to a range of interest groups (Brand *et al.*, 2002). Measures do not necessarily impact only one element of sustainability, nor do they necessarily impact all three key sustainability components positively. An intervention that effects a positive change in one aspect, does not imply that the other two aspects are necessarily positively impacted as well. The combined effects over all criteria need to be considered in a holistic, balanced and sustainable management approach.

Figure 1.5 graphically depicts the most simplified set of possible impact combinations over three criteria, for a measure (or package of measures). Here, only a fixed magnitude of impact is considered, when, in reality, the magnitude of an impact (be it positive or negative) is variable, adding further dimensionality to the problem. As shown in Figure 1.5, one of 27 potential sustainability impact combinations can materialise from any change to the system.

Assuming a rational decision-maker, the rationale behind any change to the present-day transportation system would be to improve at least one of the sustainability aspects of the system. Certain system alterations will, however, have positive impacts on more than one aspect of sustainability. It is logical that such alterations will be preferred. Similarly, all alterations will not be deemed equal when the magnitudes of the overall, combined impacts of alterations are compared. It is, thus, possible to evaluate, compare and rank various planned system alterations. Should there be only a small number of alterations to compare, this can be done explicitly by enumerative methods. If the problem exceeds enumerative capacity (which it does), the problem becomes an ideal candidate for optimisation. Measure packages that lead to improvements in terms of all three sustainability aspects, simultaneously, are referred to as ‘win-win’ options (Munasinghe, 2004). Such options are, typically, preferred and, once all ‘win-win’ options are realised, policy- and decision-makers can evaluate trade-offs among other available options.

Economic impact	Environmental impact	Social impact
+	+	+
+	+	~
+	+	-
+	~	+
+	~	~
+	~	-
+	-	+
+	-	~
+	-	-
~	+	+
~	+	~
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~	-	-
-	+	+
-	+	~
-	+	-
-	~	+
-	~	~
-	~	-
-	-	+
-	-	~
-	-	-

Legend:

+	Positive impact
~	No impact
-	Negative impact

Figure 1.5 Measure impact combinations on sustainability criteria

Several studies have been done to provide decision support in terms of developing transport energy mitigation policy. TRANSvisions (Petersen *et al.*, 2009), LTMS (Winkler, 2007), NATMAP (ASPO *et al.*, 2008) and The Future of Trucks (IEA, 2017b) are good examples of such studies. Virtually all studies in this domain resort to a scenario modelling approach, where a number of mitigation measures are cherry picked for the analysis and their levels of implementation confined to a set of predefined values, in order to contain the scope of the work. Though the comparison between measures provide some valuable insights, this approach is limited in its capacity to explore the search space, it does not really account for interactions between measures, nor does it address the system-wide impacts of measure implementation. The ability to develop coherent measure packages is also limited. Another restriction with many of these studies, is that they are often limited to only one mode of transport or one category of mitigation measures.

The STEEDS decision support system (DSS) (Brand *et al.*, 2002) is a software modelling system developed to evaluate future policy and technology options for the European transport system. It enables decision-makers to explore the long-term projections of market take-up of different transport technology mixes under the influence of different policy and technology options and exogenous macro-economic contexts and to assess their energy and environmental impacts. This is, however, a discrete evaluation method based on a pairwise comparison technique, which constrains the model's ability to explore the search space.

Zhang *et al.* (2006) and Shepherd *et al.* (2006) are some of the only examples where optimisation has been applied to gain insight into the formulation of optimal transport strategies. Their studies focused on urban, passenger transport and simplifying assumptions and workarounds were needed to offset limitations in computational ability, but the results show the value and merit in using such an approach when developing integrated transport strategies.

1.3 Research Objective

The research objective in this dissertation is to develop a decision support tool which addresses the complexities (as discussed in Section 1.2) in the formulation of freight transport energy management strategies, to ultimately facilitate the development of holistic, sustainable and comprehensive freight management policy by government level decision-makers.

1.4 Conceptual Framework of Research

The conceptual framework of the research is graphically illustrated in Figure 1.6. The research lies at the nexus between sustainable transport planning (specifically the development and implementation of transport energy demand and emissions mitigation policies), traditional transportation modelling and operations research (including optimisation modelling, simulation modelling and the science of decision-making). The research intent is to draw on existing knowledge in each of these domains and to combine this into an overall decision support tool that benefits from the strong points of each of the individual components, enabling the generation of valuable decision support on strategic freight energy management.

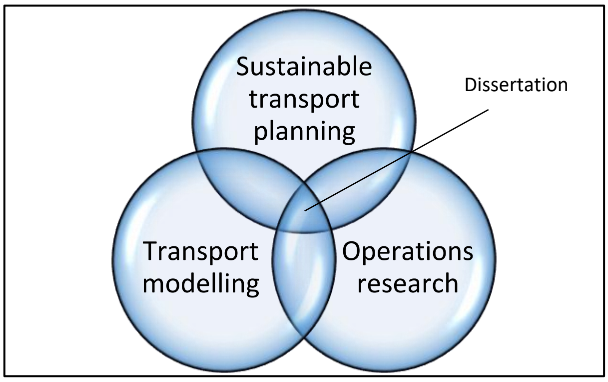


Figure 1.6 Conceptual framework of the research

1.5 Research Methodology

The standardised operations research approach, described in detail in Appendix B, is a useful and suitable methodology to employ to facilitate achievement of the objective of this study. May *et al.* (2005) indicate that the strengths of following a logical, structured approach (such as the standardised operations research approach) are: it provides a structure where participation can be encouraged at all the key stages in the decision-making process; it offers a logical basis for proposing solutions and for assessing any proposed suggestions by others; it ensures that the appraisal of alternative solutions is conducted in a logical, consistent and comprehensive way against the full set of objectives and it provides a means for assessing whether the implemented instruments have performed as predicted, enabling the improvement of prediction models. Operations research embodies the science of decision-making and is considered the appropriate discipline from which to approach the research of developing a decision support tool, presented here. The standardised operations research approach (summarised in Figure 1.7) was used as a roadmap for the development of the decision support tool in this thesis.

The research commenced with a literature review on the relationship between transport, energy and sustainability. This was followed by applying the problem formulation and mathematical formulation steps of the standardised operations research approach to the research problem. Tool selection was researched and discussed subsequently, after which solution procedure development commenced.

In this step, a generic freight network simulation model was developed to calculate the impacts of freight energy mitigation measures over the network. These impacts are measured over various sustainability indicators. The simulation model was integrated into an optimisation algorithm (Archived Multi-objective Simulated Annealing (AMOSA) developed by Bandyopadhyay et al. (2008)). The optimisation algorithm is able to make changes to measure implementation levels before the simulation model is run. The resulting sustainability impacts from this simulation run are then calculated by the simulation model and converted into objective function values, used by the optimisation algorithm to determine what changes to make next to measure implementation levels.

Figure 1.8 demonstrates the interaction between the simulation and optimisation model components of the decision support tool. The optimisation algorithm was designed to explore the search space and find a good approximation of the set of Pareto optimal solutions, where each solution corresponds to a package of freight energy mitigation measures.

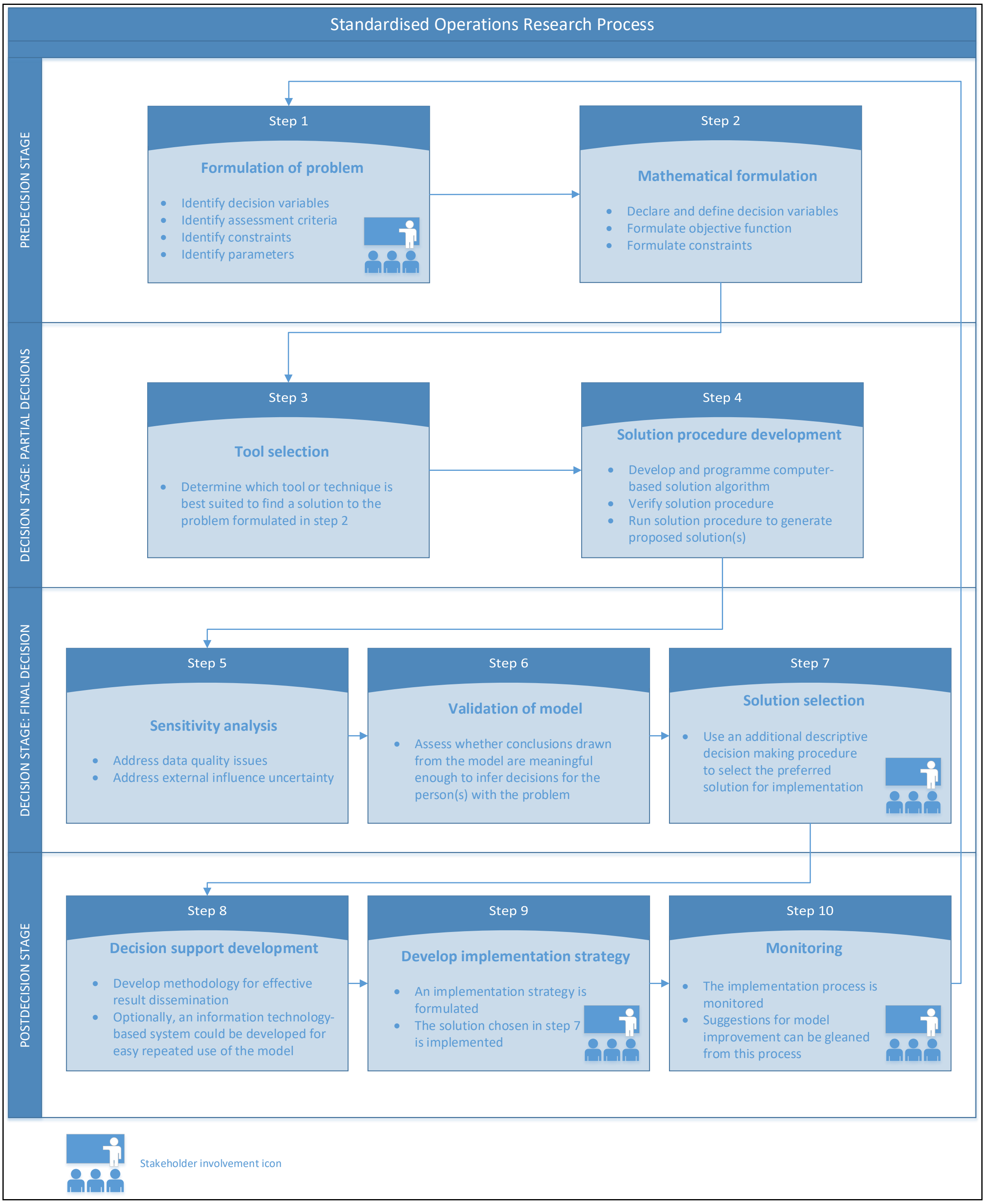


Figure 1.7 A standardised operations research process

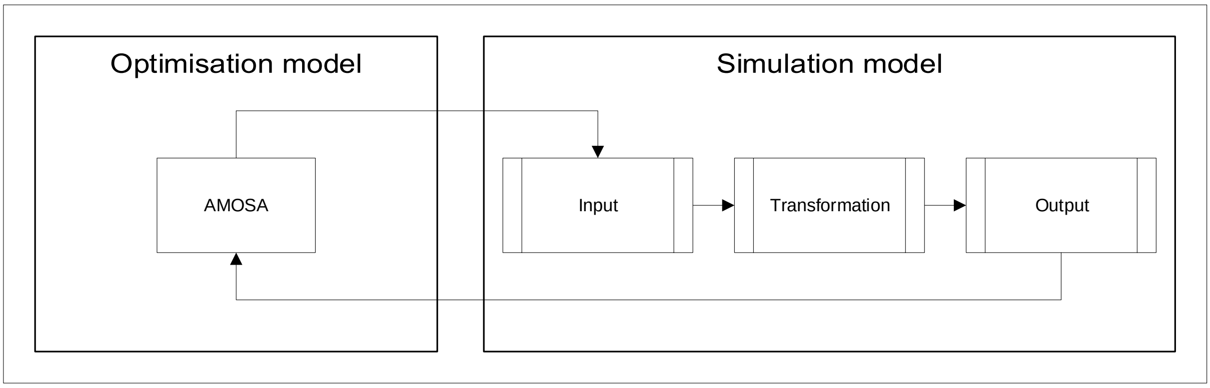


Figure 1.8 Conceptual design of the decision support tool

To demonstrate the use and usefulness of the decision support system developed, a case study version of the tool was built and discussed. Results from the case study implementation were used to verify and validate the tool and to demonstrate the decision support generated and how it can be interpreted and incorporated into a decision-making process.

The research concluded with an objective reflection on the achievement of the research objective, the strengths and weaknesses of the decision support tool that has been developed and its contribution to science. This research methodology incorporated elements from sustainable transport planning, transportation modelling and operations research, as expected from the conceptual design of the research.

1.6 Research Questions

Several research questions are addressed in this dissertation. The questions can be categorised into questions on the validity of the research premise, questions pertaining to the formulation of an appropriate decision support tool that deals with the complexities mentioned in Section 1.2, questions with regards to the outputs produced by the decision support tool and whether or not these outputs are in line with expectations, questions pertaining to the success of the decision support tool in achieving the research objective as stated in Section 1.3, questions on how the tool can be utilised in a decision-making process and questions on the case study results to demonstrate the information generated by the tool. Table 1.4 contains a list of all the research questions addressed in the dissertation and indicates in which chapter the questions are addressed.

Table 1.4 List of research questions addressed in this dissertation

Category of Research Questions	**Research Questions**	**Chapter Addressing Question**
Validity of research	1.1 Does freight energy management significantly affect freight transport sustainability?	2
	1.2 Is operations research a suitable discipline from which to approach the research?	1
Formulation of the decision support tool	2.1 How should freight energy management policies and measures be converted into modelling decision variables?	3
	2.2 How can measures of all types and varying scope be accommodated into one single model?	5
	2.3 What model specification will allow unknown, future measures to be accommodated?	5
	2.4 What model specification will allow the inclusion of any number of measures?	5
	2.5 What model specification will be able to accommodate variable implementation levels per measure?	5
	2.6 How should the interaction between measures be represented in the model?	5
	2.7 What model specification will enable the formulation and exploration of measure combinations?	5
	2.8 How can both continuous and discrete variables be accommodated into one single model?	5
	2.9 What model specification will allow for a fair comparison of measure impacts?	5
	2.10 How should sustainability assessment indicators be converted into objective functions?	3
	2.11 What model specification will avoid double counting of measure impacts?	5
	2.12 What model specification will account for the knock-on effects of measure implementation?	5
	2.13 What model specification will accommodate multiple objectives?	5

	2.14 What constraints should be included in the model and should they be modelled implicitly or explicitly?	3
	2.15 What are the data requirements of the tool?	3
	2.16 Which decision support modelling tool is the most appropriate?	4
	2.17 Is the model transparent and tractable?	5
Decision support tool outputs	3.1 Is the simulation optimisation modelling methodology appropriate?	4
	3.2 Are all solutions equivalent, or are some solutions better or worse than others?	6
	3.3 Does a Pareto frontier (and, thus, a trade-off between solutions) exist?	6
	3.4 Are packages of measures more effective than individual measures?	6
	3.5 Is the search space sufficiently explored?	6
	3.6 Does the model converge towards the Pareto frontier?	6
	3.7 What is the quality of the solution found by the tool?	6
	3.8 How does the tool deal with uncertainty and how robust are the solutions generated by the tool?	6
Success of the decision support tool	4.1 Does the decision support tool produce valuable decision support?	6
	4.2 How do the outputs from the decision support tool facilitate better decision-making?	6
	4.3 Is the tool practical to use for its intended purpose?	6
Case study	5.1 What combinations of measures are preferred from different stakeholder perspectives?	6
	5.2 How do Pareto optimal measure combinations differ?	6
	5.3 Are there any measures that are always preferred for inclusion in the Pareto front (at a particular level of implementation), or that are never included?	6
	5.4 What are the trade-offs that decision-makers need to debate?	6

	5.5 Can the findings from the case study model be generalised into rules of thumb?	6

1.7 Scope of Research

The scope of the decision support tool developed is contained to a strategic level and the tool can be categorised as a sketch planning model. Sketch planning models assist policy makers in making long term, strategic decisions and estimates overall effects, often on a provincial or national level (Vanderschuren, 2007). They are static in nature, meaning they provide a snapshot view of the system and not a dynamic one. Figure 1.9 demonstrates the domain of sketch planning models, compared to other transport modelling types. Tactical and operational issues fall beyond the scope of this research.

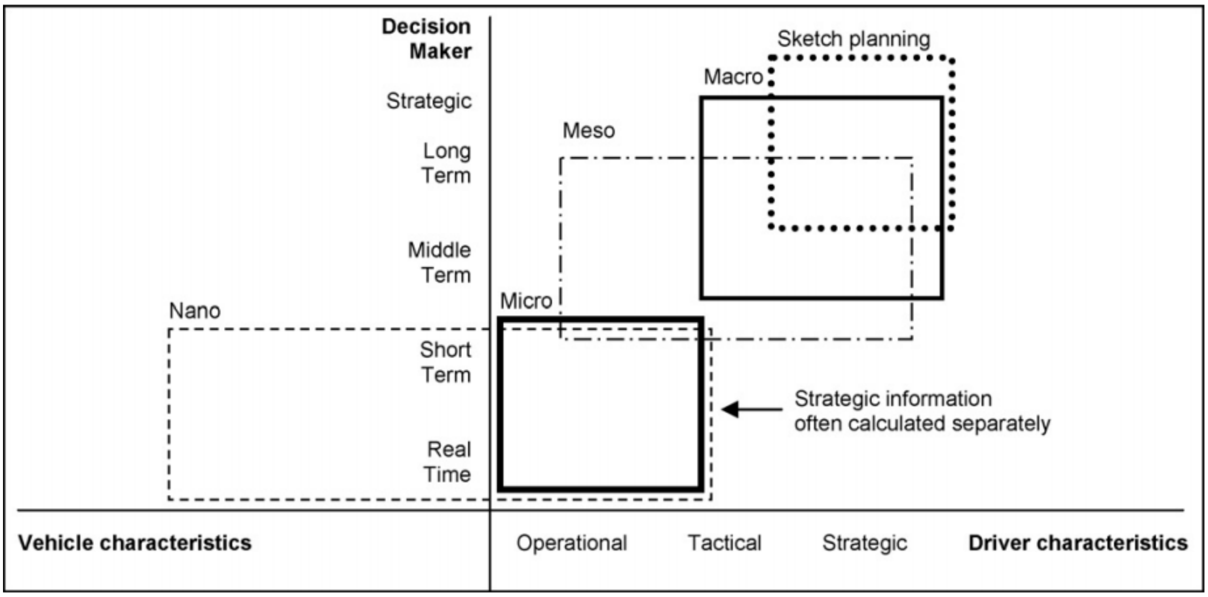


Figure 1.9 Levels of decision-making in transport modelling (Vanderschuren, 2006)

The tool is developed to support decision-making by providing information on what policies should aim to achieve, however, no insights to the practical policy formulation process, or implementation of policy, is included in this research. The scope of this work is restricted to policies that affect the energy demand of freight transportation on a regional or national scale. Urban freight policies are excluded from this study. Only the energy demand of the actual transportation activity is addressed - the indirect energy demand from the production of fuels, vehicle manufacturing, infrastructure construction, or similar secondary sources of energy demand are not included in the analysis at this point in time.

The purpose of the case study presented is to serve as a proof of concept only; it is intended to be an illustrative example of the decision support tool in a real-world application, but does not serve as a real-world application in itself. There was no client for the study, hence, there was no stakeholder involvement, as there would have been in a real-world application. Steps eight through ten of the standardised operations research approach (described in Appendix B), consequently fall beyond the scope of this research.

1.8 Research Design Classification

The research can be categorised as an empirical study where existing data (ranging from numeric to textual) is analysed with a low to moderate degree of control. The study can be classified as a model-building study, based on the research typology developed by Mouton (2001), with an inductive approach being followed. The key purpose of using modelling in this research is to bring conceptual coherence to this domain of science, in support of facilitating better decision-making.

1.9 Document Outline

The remainder of this document can be divided into three distinct sections. The first section, Chapter Two, contains literature reviews on, and exploration of, the key topics of this dissertation. Chapter Two delves into the relationship between transport, energy and sustainability. The second section (Chapters Three through Five) describes the development of the decision support tool. The problem formulation is laid out in Chapter Three, followed by a discussion on selecting the appropriate modelling tool(s) in Chapter Four. Chapter Five contains a detailed overview of the formulation of the optimisation and simulation models that constitute the decision support tool. The final section in the document showcases the results produced by the tool and how they facilitate decision-making (discussed in Chapter Six). Conclusions on the research presented and opportunities for follow-on studies are presented in Chapter Seven.

2 The Relationship between Transport, Energy and Sustainability

Transportation is an essential part of modern existence. Since the beginning of human history, transport has been an engine of growth (Greene and Wegener, 1997). Without transport, there would have been no trade, nor cities. The Roman Empire was built on efficient highways and the wealth of Venice on Mediterranean trade routes. Roads were a fundamental tool in helping Rome rule the Ancient World (Andrews, 2014), whereas, without high sea navigation, there would not have been a British Empire and America would have remained undiscovered; without railways the American West would not have been settled (Greene and Wegener, 1997). Interestingly, South Africa also owes its origins to its strategic location along global trade routes.

Modern economies cannot exist without the goods and services provided by cars, trucks, trains, airplanes and other transportation alternatives. Transport is, however, somewhat different from other economic sectors – it is a product of the need for some other activity and is, therefore, seen as a derived demand. The need for transportation is born from the need to connect entities, such as supply and demand, or desire and the fulfilment of that desire, making it an enabler of the modern way of life.

The provision of transportation services and the essential enabling properties thereof does, unfortunately, come at a price. The challenge at hand is to enable transport to contribute to the increase in economic well-being of citizens across the world (especially in developing countries), whilst containing its negative consequences (Bongardt *et al.*, 2013). The realisation of a sustainably operational transportation system is the common goal of transport planners and managers all over the world, because it is recognised that this is the only defensible and justifiable modus operandi to be followed in the modern era.

Dalkmann *et al.* (2011) outlined a sustainable transport system to comprise the following components:

- *environmental sustainability* is achieved by protecting the global climate, ecosystems, natural resources and public health;
- *economic sustainability* is achieved by providing affordable, fair and efficient transport that supports economic activity, as well as balanced regional development and the creation of jobs; and, finally,

- *social sustainability* is achieved by allowing the basic access and development needs of individuals, companies and society to be met safely and in a manner consistent with human health and by promoting poverty reduction and equity within and between successive generations.

Dalkmann's definition subscribes to the standardised definition of sustainable development, as published by the World Commission on Environment and Development (1987), which reads: "Sustainable development is one that meets the needs of the present without compromising the ability of future generations to meet their own needs". Another, more pragmatic, definition of sustainable development is provided by Daly (1991). He defines a sustainable development as one that satisfies three basic conditions: its rates of use of renewable resources do not exceed their rates of regeneration, its rates of use of non-renewable resources do not exceed the rate at which sustainable renewable substitutes are developed and its rates of pollution emission do not exceed the assimilative capacity of the environment. Although there is global consensus that developments should be environmentally conscious, there is also agreement that a merely environmental definition of sustainability (such as Daly's) is not sufficient (Greene and Wegener, 1997). "Greening is not the only important thing: beyond greening lies the challenge of developing a sustainable global economy; an economy that the planet is capable of supporting indefinitely" (Hart, 1997).

Eißel and Chu (2013) state that the overall sustainable transport management aim is to disconnect mobility from its adverse effects - to develop a transport system that responds to the needs of the economy to transport goods, while anticipating resource and environmental constraints. The externality cost of transport is difficult to calculate, as there are various hidden elements to consider; it is far reaching, spanning a variety of elements (from the environment through industrial productivity) and is not, necessarily, paid in an equitable manner. Those who typically cause the negative externalities of transport, and those who are normally affected, are unevenly distributed across socio-economic groups, both within one country and across countries or world regions. Equity among generations, nations and individuals is, generally, regarded as integral to the definition of sustainability (Greene and Wegener, 1997).

It is important to integrate and reconcile the economic, social and environmental impacts of transport within a holistic and balanced sustainable development framework, as Munasinghe (2004) suggests. Figure 2.1 highlights some of the benefits of achieving sustainable transport, supporting the notion that all three pillars of sustainability are affected by transportation.

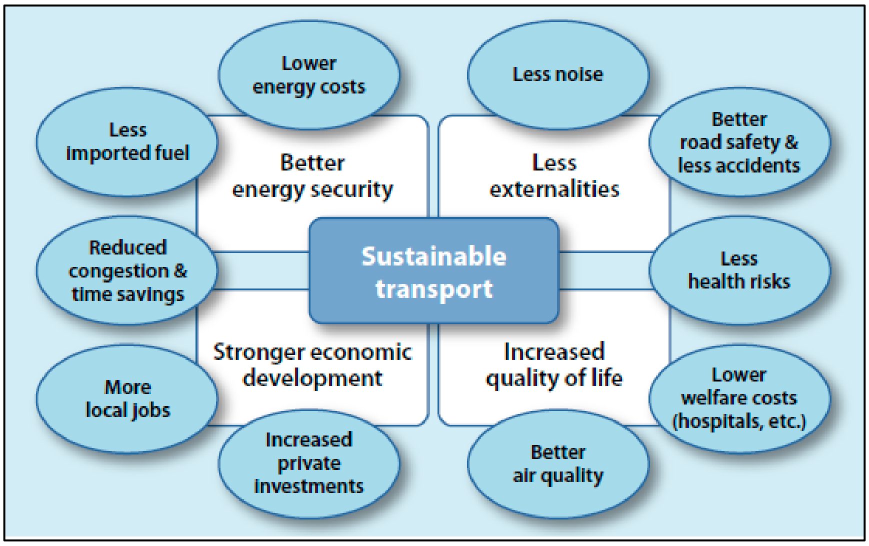


Figure 2.1 Benefits of sustainable transport (GIZ, 2011)

The energy sector, in turn, also critically interacts with the economic, social and environmental dimensions of sustainable development (Munasinghe, 2004). Firstly, energy has long been perceived as a major driving force underlying economic progress and economic growth itself further stimulates energy demand. Secondly, energy production and use are strongly interlinked with the environment and, thirdly, energy is essentially a basic human need today, because access to energy significantly affects social well-being. Akin to transportation's enabling effects on economic activity, energy is an enabler of transport. Without some form of energy expenditure, to initiate and sustain propulsion, transportation would not be possible. Energy and transportation are, thus, inextricably intertwined. This implies that the energy used to power the transportation sector has major implications on transport sustainability.

Regrettably, the reality is that the energy source predominantly used to power the world's transportation today, is oil - a non-renewable, fossil-based, highly polluting energy source. Approximately 92% of global transport is fuelled by oil (Table 2.1). Transport is, in fact, the sector that is the largest consumer of oil globally (Figure 2.2), growing from 45.3% of the 2 252 million tonnes of oil equivalent (Mtoe) total world oil demand in 1973, to 64.9% of the 3 840 Mtoe demanded in 2015 (IEA, 2017a). This growth was driven by a growth in world oil demand from aviation (2.1%) and road transport (18.9%) over this period. Rail transport appears to be somewhat less oil dependent in 2015, with world oil demand from rail dropping by 0.9% since 1973.

Worldwide, between 43% and 47% of transport energy use is required for the movement of freight (MIT and Charles River Associates, 2001; Gilbert and Perl, 2008). It is important to note that the volume of global freight movement is rising at a faster pace than the volume of people movement.

Energy use in IEA countries' surface freight has increased by 80% between 1973 and 2004, compared to a 45% growth in passenger transport energy use over the same period (IEA, 2004). Trucks were responsible for nearly 40% of the growth in global oil demand between 2000 and 2015 (Figure 2.3). Without further policy efforts, trucks are expected to account for 40% of oil demand growth and 15% of the increase in global energy-sector carbon dioxide (CO_2) emissions up to 2050 (Teter, 2018).

Table 2.1 Energy supply split to the transport sector in 2015 (IEA, 2017a)

Fuel	**Transport sector consumption as percentage of total world fuel consumption per fuel**	**Absolute transport sector consumption per fuel (Mtoe)**	**Percentage of transport sector energy supply from fuel**
Biofuels and waste	7.22%	75.99	2.81%
Coal	0.24%	2.53	0.09%
Crude oil and oil products	64.88%	2491	92.16%
Geothermal, solar, wind, heat and electricity	1.75%	35.9	1.33%
Natural gas	6.97%	97.59	3.61%

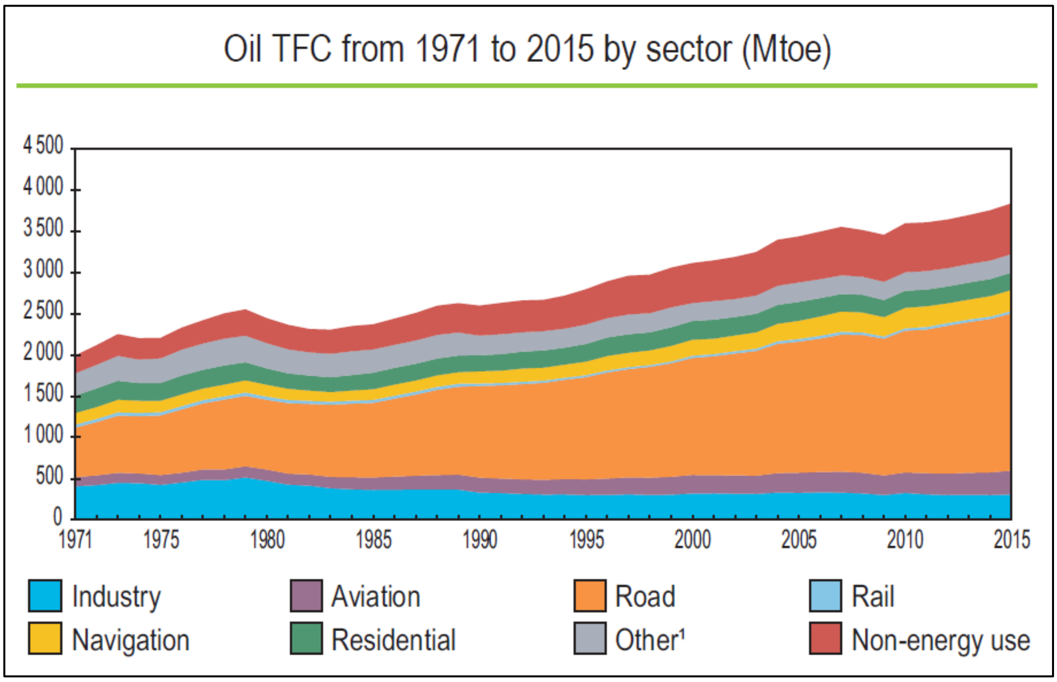


Figure 2.2 World oil consumption per sector (IEA, 2017a)

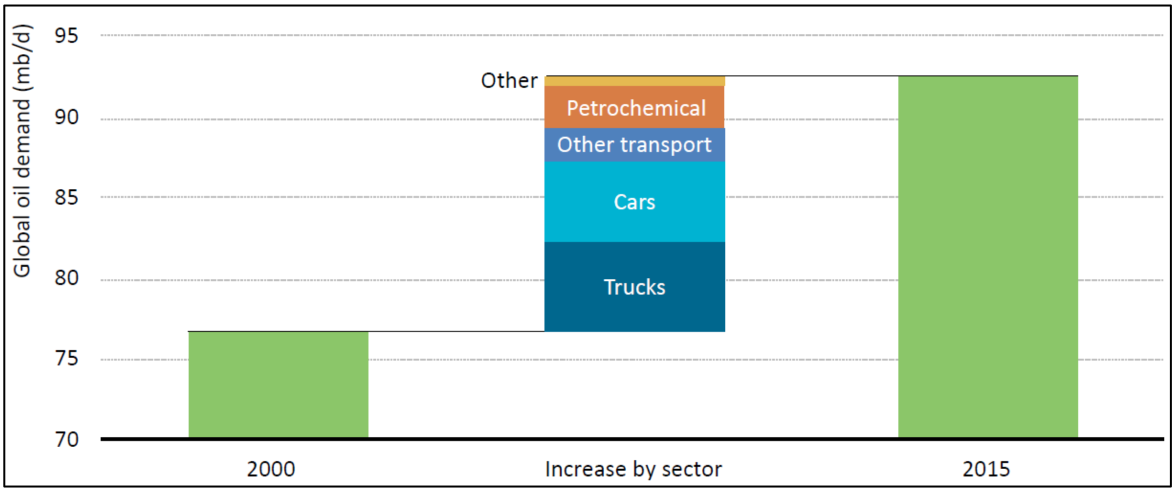
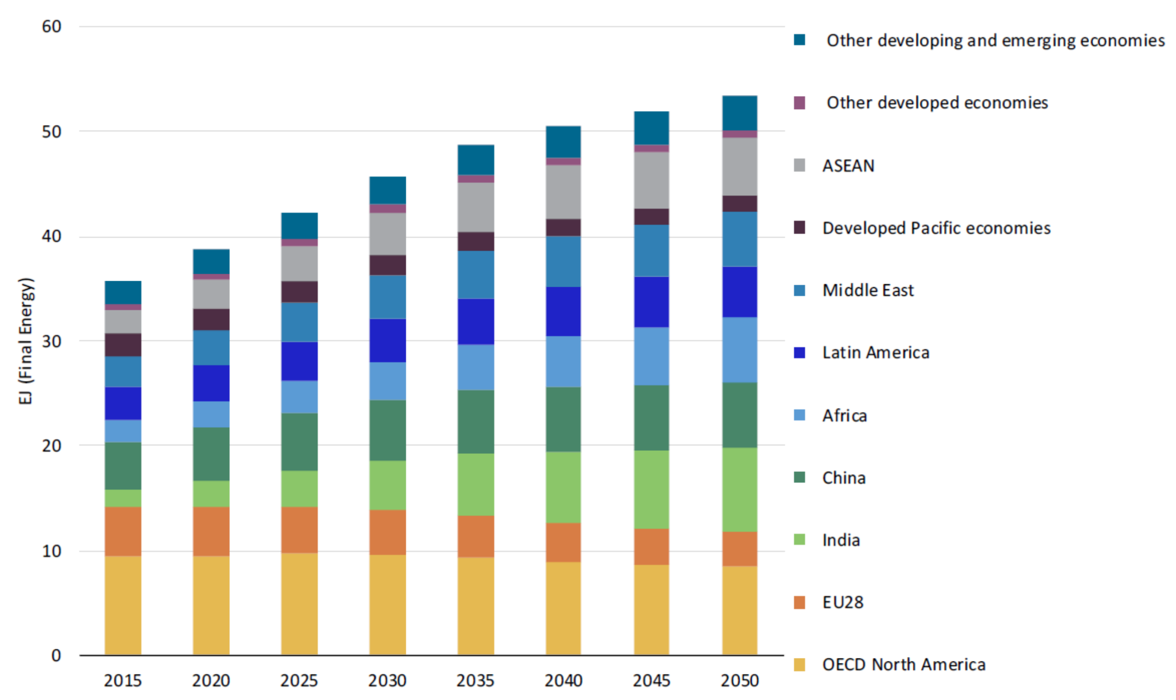


Figure 2.3 Impact of trucks on global oil demand (Teter, 2018)

Overall trucking energy intensity has declined significantly in merely a few countries since 1973 (IEA, 2004). In other countries, individual truck efficiencies have likely improved, but this effect may have been offset by changes in the size-mix of trucks and the nature of the loads they carry. For example, in the United States, the average weight of truck shipments has declined - perhaps due to moving more light-weight products. This can result in an increase in energy use per tonne (and tonne-kilometre) shipped. On the other hand, in Australia, where trucking intensity did fall significantly, there has been strong growth in very large long-haul trucks that carry heavy loads very efficiently (IEA, 2004). The operational aspects of freight transport is another important element of freight energy demand and should not be underestimated.

The world's need for freight transportation is expected to continue to grow, going forward. The European Union expects freight transport volumes to grow by almost 90% by 2050 (Enei, 2010). The IEA predicts that transport demand for oil will grow steadily (IEA, 2012) and perhaps by as much as 40% by 2035 (IEA, 2013b). Gilbert and Perl (2008) indicate that the use of oil for transport has been rising at a higher rate than use of oil for any other purpose. They mention that the IEA projects a continuation of this difference and that oil use for transport is expected to grow by 52% between 2004 and 2030, while oil for other purposes is expected to grow by 29% during that period. Interestingly, the growth in annual oil use for transport is expected to come from the developing world only. Figure 2.4 shows the IEA's reference scenario projections for energy demand growth from trucking in different world regions. A decline in developed world energy demand is more than offset by the growth from the developing world regions.



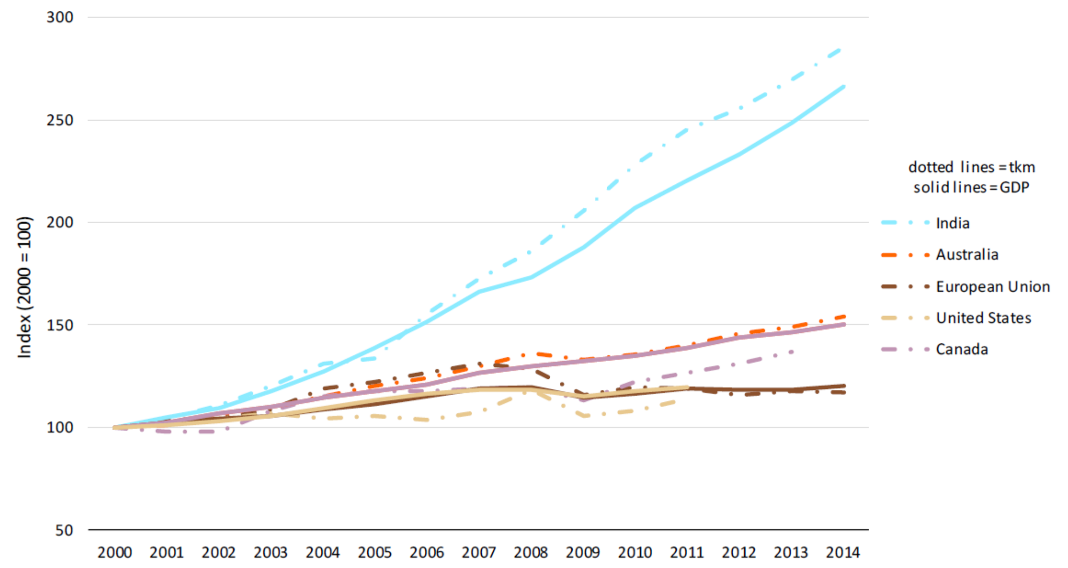
Source: IEA (2017a), Mobility Model, June 2017 version, database and simulation model, www.iea.org/etp/etpmodel/transport/.

Figure 2.4 Energy demand growth from road freight vehicles by region in the IEA Mobility Model June 2017 version Reference Scenario (IEA, 2017b)

2.1 How Freight Energy Use Affects Economic Sustainability

Being a fundamental component of a successful economy, transport has often determined the location of industries and cities and the prosperity of regions. The spatial sciences have equated accessibility and mobility with economic and social progress (Greene and Wegener, 1997). Moreover, in most industrial countries, transport has established itself as a major industry, intricately linking it to the well-being of the national economies (Greene and Wegener, 1997). Comparing freight transportation volumes (in tonne-kilometres or tkm) to an indicator of economic health - gross domestic product (GDP) - there appears to be a strong correlation between freight transport growth and economic growth, as demonstrated in Figure 2.5.

A key concern regarding economic sustainability is whether freight costs will remain low enough for national and international trade to continue to prosper (MIT and Charles River Associates, 2001). Fuel (energy) is the biggest contributor to road transport costs in South Africa, accounting for 31.7% of transport costs in 2015 (Havenga *et al.*, 2015). With the freight sector almost entirely dependent on oil as its energy source, the sector is highly exposed to price shocks in the oil industry. Such shocks can come about as a result of international political conflict, market forces artificially influencing the global oil price, outright scarcity of oil as a resource and competition from new (potentially unforeseen) oil consumers, amongst others. Figure 2.6 depicts the historic growth and volatility in average crude oil prices for three different benchmark crude oils: North Sea Brent, Dubai and West Texas Intermediate (WTI). South African fuel prices have seen a drop of 4.87%, followed by an increase of 17.13%, in the first nine months of 2018 (AA, 2018).



Note: GDP = gross domestic product.

Sources: Department of Infrastructure and Regional Development (2013); NATS (2016); Eurostat (2016); Japan Statistics Bureau (2014); Bureau of Transportation Statistics (2016); Ministry of Road Transport & Highways (2016); World Bank (2016); OECD (2016); IEA (2016c).

Figure 2.5 Indexed evolution of road freight activity versus GDP in selected regions (IEA, 2017b)

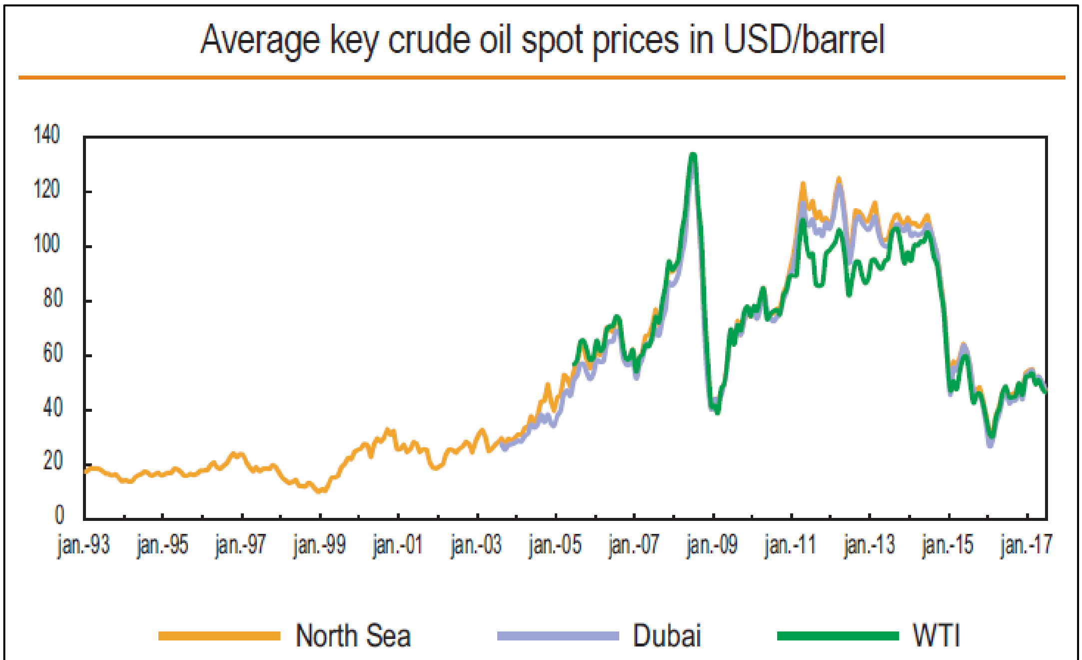


Figure 2.6 Crude oil price volatility (IEA, 2017a)

Oil was formed by geological processes millions of years ago and is typically found in underground reservoirs of dramatically different sizes, at varying depths and with widely varying characteristics. The largest oil reservoirs are called "Super Giants", many of which were discovered in the Middle East. Because of their size and other characteristics, Super Giant reservoirs are generally the easiest to find, the most economical to develop and the longest lived. The last Super Giant oil reservoirs discovered worldwide were found in 1967 and 1968. Since then, smaller reservoirs of varying sizes have been discovered in what are called "oil prone" locations worldwide - oil is not found everywhere (Hirsch *et al.*, 2005).

The earth's endowment of oil is finite and demand for oil continues to increase with time. Accordingly, geologists know that at some future date, conventional oil supply will no longer be capable of satisfying world demand (Hirsch *et al.*, 2005). At that point, world conventional oil production will have peaked and begin to decline. No one knows with certainty when world oil production will reach a peak, but geologists have no doubt that it will happen. It is important to recognise that oil production peaking is not equivalent to oil reserve depletion. Peaking occurs when a reservoir's maximum oil production rate is achieved, which typically occurs after roughly half of the recoverable oil in a reservoir has been produced (Hirsch *et al.*, 2005). When world oil production peaks, there will still be large reserves remaining. Peaking means that the rate of world oil production cannot increase; it also means that production will, thereafter, decrease over time. Even though oil might still be physically available and abundant in the near future, if oil should become unaffordable, oil will be rendered just as inaccessible to some (mainly poorer) countries as if a physical shortage were to exist.

Oil production has, over time, undergone momentous shifts below ground. The impact of innovative production technologies on supply has been larger than expected and truly transformative. At the same time, unplanned maintenance and technical disruptions at mature fields have reached an unprecedented scope, rekindling concerns about decline rates in ageing plays (IEA, 2012). The capacity of technologies to unlock new types of resources, such as light tight oil (LTO) and ultra-deepwater fields, as well as to improve recovery rates in existing fields, is pushing up estimates of the amount of oil that remains to be produced (IEA, 2013a).

In the World Energy Outlook 2013 (IEA, 2013a), the IEA projected future developments in the energy sector up to 2035. The need to compensate for declining output from existing oil fields is expected to be the major driver for upstream oil investment. An analysis of more than 1 600 fields confirmed that, once production has peaked, an average conventional field can expect to see annual declines in output of around 6% per year. While this figure varies according to the type of field, the implication is that conventional crude output from existing fields is set to fall by more than 40 million barrels per day by 2035. Among the other sources of oil, most unconventional plays are heavily dependent on continuous drilling to prevent rapid field-level declines. Of the 790 billion barrels of total production required to meet the projections for demand to 2035, more than half is needed just to offset declining production (IEA, 2013a).

Bearing in mind that oil supply will begin to dwindle at some point, it is alarming that world oil demand is expected to grow 50% by 2025 (U.S. Department of Energy, 2004). Under business-as-usual conditions, world oil demand is expected to continue to grow, increasing approximately two percent per year for the next few decades (Hirsch *et al.*, 2005). This growth will be driven primarily by the transportation sector, as mentioned. The economic and physical lifetimes of existing transportation equipment are measured on decade time-scales and, since turnover rates are low, rapid changeover in transportation end-use equipment is inherently impossible. Trucks, aircraft and ships simply have no ready alternative to liquid fuels, at present. Non-hydrocarbon-based energy sources, such as solar, wind, photo-voltaic, nuclear power, geothermal power, fusion, etc. can produce electricity, not liquid fuels, so their widespread use in transportation is, at best, decades away (Hirsch *et al.*, 2005). Additionally, the cost of generating renewable energy is, potentially, greater and the yields lower than their fossil-based alternatives.

Hirsch *et al.* (2005) performed a study on the mitigation efforts that will be required in a peak oil eventuality and they concluded the following: waiting until world oil production peaks before taking crash programme action would leave the world with a significant liquid fuel deficit for more than two decades. Initiating a mitigation crash programme 10 years before world oil peaking helps considerably, but still leaves a liquid fuels shortfall roughly a decade after the time that oil would have peaked. Initiating a mitigation crash programme 20 years before peaking, in turn, appears to offer the possibility of avoiding a world liquid fuels shortfall for the forecast period. Hence, with adequate, timely mitigation, the economic costs to the world can be minimised. If mitigation efforts were to be too little, too late, world supply and demand balance will be achieved through massive demand destruction (shortages), which would translate to significant economic hardship (Hirsch *et al.*, 2005).

The world has never faced a problem like this. Without massive mitigation more than a decade before the fact, the problem will be pervasive and will not be temporary (Hirsch *et al.*, 2005). Previous energy transitions (wood to coal and coal to oil) were gradual and evolutionary; oil peaking will be abrupt and revolutionary. Mitigation will require an intense effort over decades. This inescapable conclusion is based on the time required to replace vast numbers of liquid fuel consuming vehicles and the time required to build a substantial number of substitute fuel production facilities (Hirsch *et al.*, 2005).

Although a considerable debate on oil peaking has been active since the first discovery of oil, it is important to realise that shifting to a different non-renewable energy source will ultimately yield the same depletion scenario, followed by a forced transition to a new energy source. Such energy sources might, thus, buy some time to transition away from oil, but are not permanent solutions.

Another supply side concern for the price of fuel is the above ground risks facing the oil market. These include continued political upheaval in the Middle East and North Africa - disrupting crude exports from several countries and reducing crude oil availability, due to the implementation of expanded international sanctions on oil exporters (IEA, 2012).

To summarise: the transport sector's gross reliance on fossil-based, non-renewable energy is a great threat to economic sustainability. Daly's definition of sustainable development advises that the rate of use of non-renewable resources must not exceed the rate at which sustainable renewable substitutes are developed and, where renewables are used, the rate of use of renewable resources must not exceed their rates of regeneration (Daly, 1991). Brandt *et al.* (2013), however, warns that an oil scarcity should not be the sole concern and that the focus should include the environmental, social and economic impacts of that with which oil will be replaced.

2.2 How Freight Energy Use Affects Environmental Sustainability

The world (and its transportation) is addicted to fossil-based energy, with coal, oil and natural gas accounting for 81.4% of total primary energy supply in 2015 (IEA, 2017a). Consequent to this energy supply mix, emissions of carbon dioxide have grown substantially as the world's demand for energy has grown (Figure 2.7), from 15.5 Mt of CO_2 in 1973, to 32.3 Mt of CO_2 in 2015 (IEA, 2017a). Emissions have more than doubled in the past 40 years. Oil accounted for 34.6% of the emissions from fuel combustion in 2015 (IEA, 2017a).

Although energy supply and consumption generate several types of environmental pollution, the major impact is on the earth's atmosphere. In May 2013, CO_2 levels in the earth's atmosphere exceeded 400 parts per million for the first time in several hundred millennia (IEA, 2013c). The weight of scientific analysis shows that the earth's climate is already changing and that extreme weather events (such as storms, floods and heat waves) should be expected to become more frequent and intense, along with increasing global temperatures and rising sea levels.

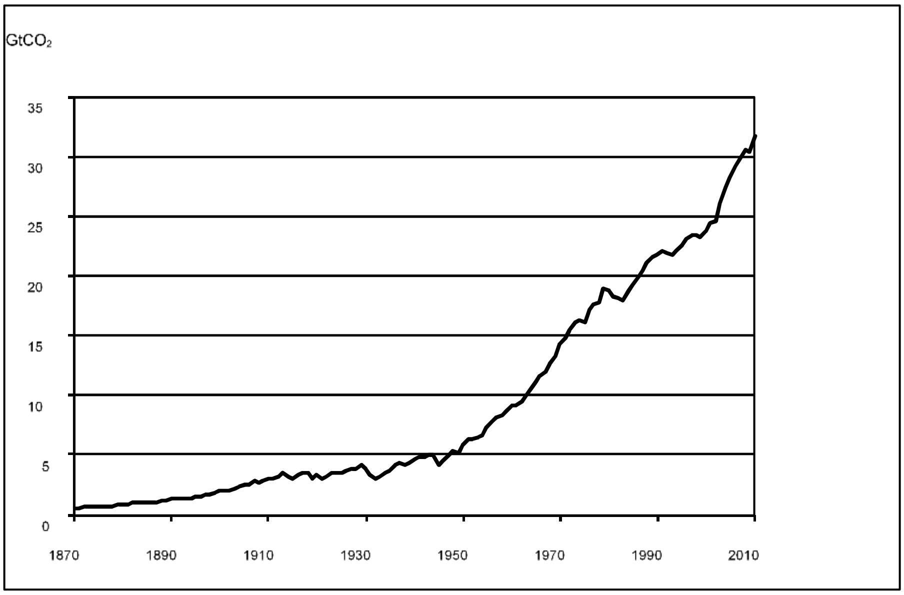


Figure 2.7 Historic trend in CO_2 emissions from fossil fuel combustion (IEA, 2013b)

In the Intergovernmental Panel on Climate Change's (IPCC) 2014 Synthesis Report (IPCC, 2014), scenarios called Representative Concentration Pathways (RCPs) are developed for making projections. RCP2.6 is a stringent mitigation scenario that aims to keep global warming likely below 2°C above pre-industrial temperatures and RCP8.5 a scenario with very high GHG emissions. Figure 2.8 illustrates the expected impacts of the different levels of global warming associated with RCP2.6 and RCP8.5, respectively, on average surface temperatures, average precipitation and average sea levels between 2081 and 2100. Even in the most optimistic RCP2.6 scenario, the impacts will be substantial for parts of the globe.

Climate change research is showing that the earth's environment is not able to absorb the volume of GHG emissions currently produced. The Fifth Assessment Report from the IPCC (Working Group I) categorically states that human influence on the climate system is clear (IPCC, 2013). Among the many human activities that produce greenhouse gases, the use of energy represents by far the largest source of emissions (83%) (IEA, 2013b). Within the energy sector, CO_2 emissions resulting from the oxidation of carbon in fuels during combustion, dominates the total GHG emissions. Yet, Daly's sustainable transport definition dictates that a sustainable transport system's rates of pollution emission must not exceed the assimilative capacity of the environment (Daly, 1991). Oil-driven freight transport is, thus, making the current energy configuration of the transport sector highly unsustainable.

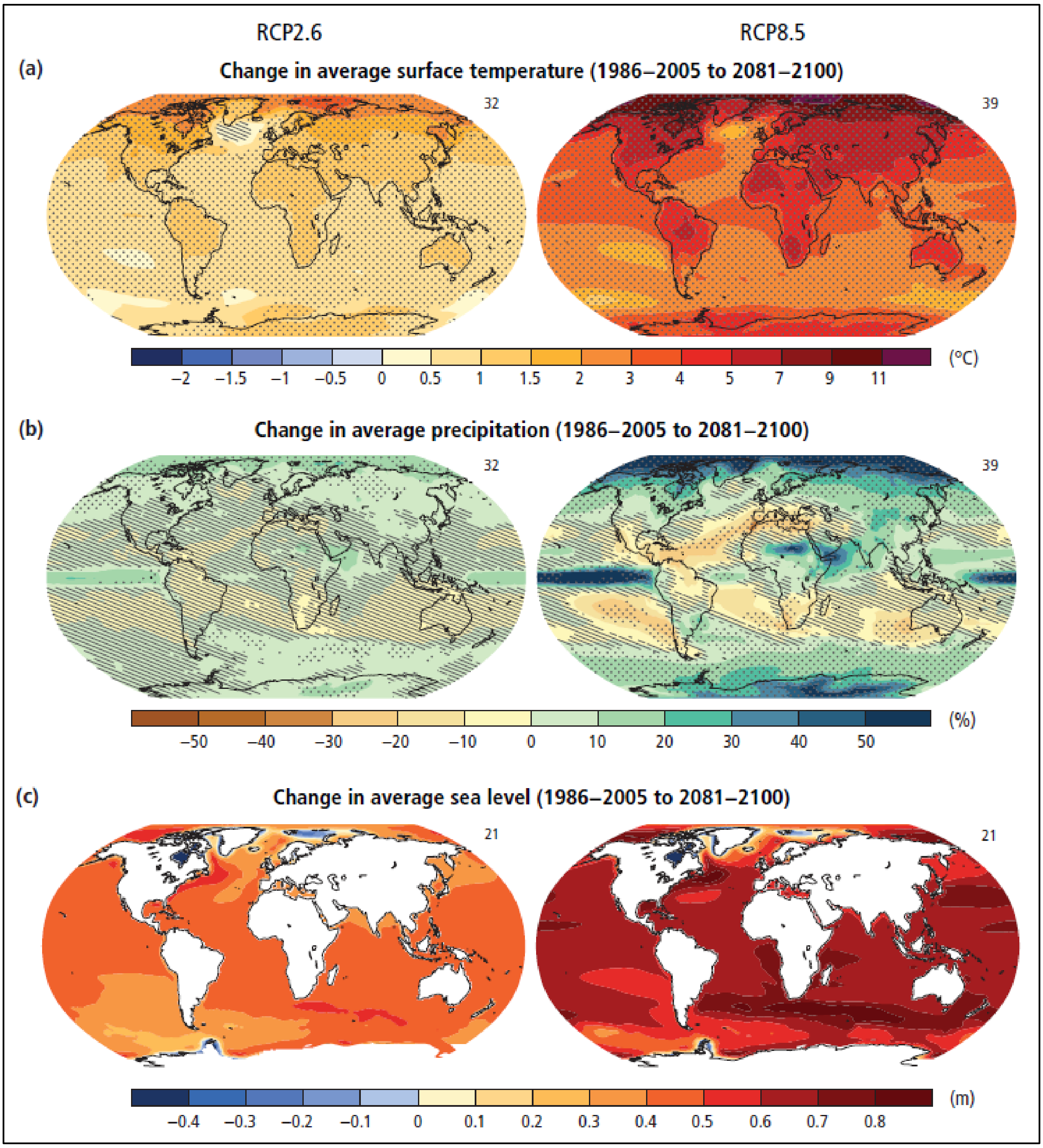


Figure 2.8 IPCC global warming scenarios and the effects on average surface temperature, average precipitation and average sea level (IPCC, 2014)

CO_2 emissions from transport, the largest end-use sector source, were just under 7 Gt in 2011 (IEA, 2013c), accounting for 22% of global emissions (IEA, 2013b). Emissions by the sector have increased by 1.7% per year, on average, since 2000, but with differing underlying regional trends. The fast emissions growth was mostly driven by emissions from the road sector, which increased by 52% since 1990 and accounted for about three quarters of transport emissions in 2011 (IEA, 2013b). Figure 2.9 shows the extensive contribution from road transport to total emissions. While passenger transport currently dominates overall GHG emissions and environmental impacts, freight transport's impacts are increasing at a higher rate (Kahn Ribeiro *et al.*, 2007).

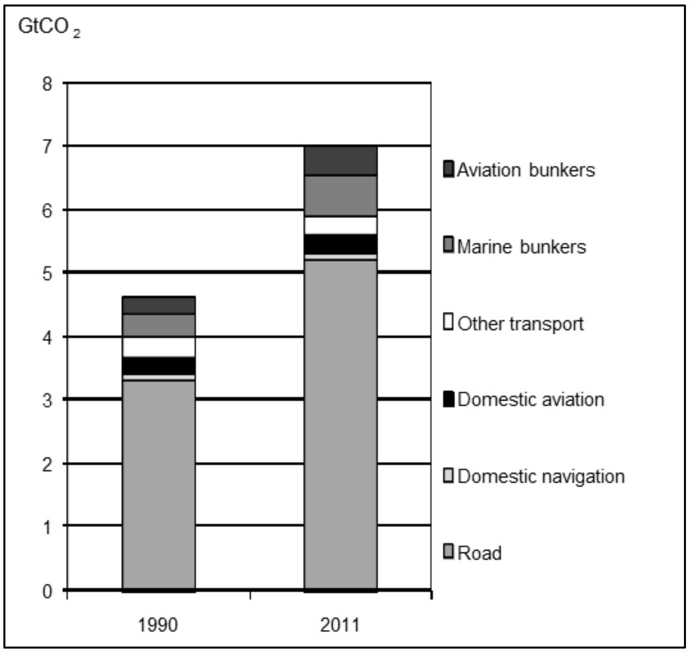


Figure 2.9 CO_2 emissions from various transport modes (IEA, 2013b)

The GHG emissions produced by the transportation sector can be predominantly ascribed to the gross dependency on oil as an energy source for the sector. It is possible to substitute some of transportation's oil consumption with natural gas or with coal (which is transformed into liquid fuels through coal-to-liquids production processes), but in terms of environmental impacts (CO_2 emissions) not much, if anything, will be gained. Coal combustion emits more emissions per unit of energy produced than any other energy source. A more promising alternative would be to substitute the use of oil for propulsion with the use of electricity. Many rail systems are already using this source of energy, but the large-scale conversion of other freight modes to electricity is not viable at present - neither operationally, nor technically. Furthermore, not all electricity consumption is environmentally cleaner than oil consumption. Most of the electricity generated globally use fossil-based feedstock (Figure 2.10), which can, potentially, be more polluting than oil. Unless an energy supply shift to renewably generated, clean energy comes into effect, an energy supply shift will not be very useful in terms of curbing GHG emissions, or the effects on climate change.

Sustained increases in anthropogenic emissions and accumulations of GHGs will significantly perturb the earth's atmosphere, affecting, in turn, the environment of every living organism on the planet.

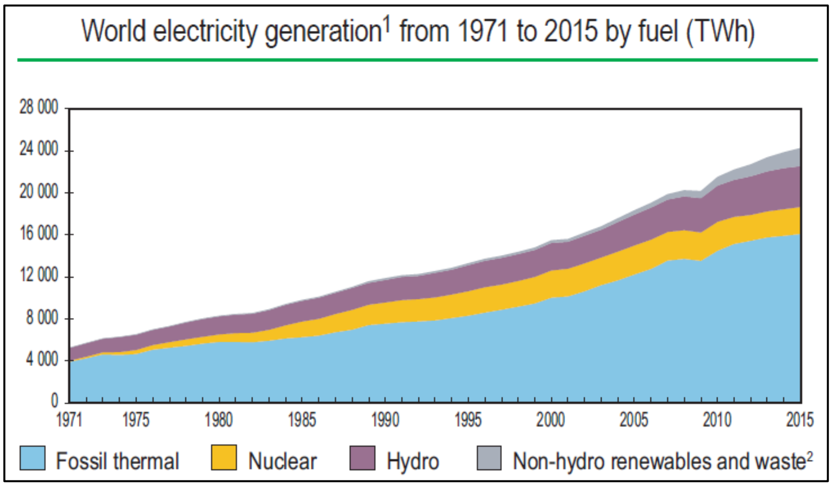


Figure 2.10 Global electricity generation methods from 1971 to 2015 (IEA, 2017a)

2.3 How Freight Energy Use Affects Social Sustainability

A sustainable freight transport sector will allow continued growth, development and improvement in the quality of life worldwide (MIT and Charles River Associates, 2001). The current dependence on high risk, finite resources to power the freight sector exposes society to the risk of a freight system collapse, which will have a devastating impact on quality of life. Stigka *et al.* (2014) state that an important effect of investing in renewable energy sources is an increase in the safety and reliability of the energy supply.

A tarnished atmosphere, resulting from freight transport related emissions, has negative impacts on societal health and well-being (Akella *et al.*, 2009; Machol and Rizk, 2013; Olson and Lenzmann, 2016). Links between human exposure to oil and gas related air pollutants and mortality, cardiovascular diseases, respiratory diseases, asthma visitations and hospitalisations, reduced lung function and lung cancer are well documented in the literature (Olson and Lenzmann, 2016). Olson and Lenzmann (2016) report that air quality tests, taken in the vicinity of US unconventional drilling sites, identified 36 chemicals that may affect the sinus, skin, ear, nose, mouth or eyes, or cause neurological symptoms; 21 that may induce behavioural effects or affect the brain or nervous system; 28 that have been associated with liver or kidney damage, or digestive or stomach problems; as well as 9 that may affect the heart, muscles or blood cells. Human exposure to poly-aromatic hydrocarbons may also cause cancer, impair the development of human foetuses, cause birth defects or changes to human DNA, or cause reproductive damage, immune system disfunction and endocrine disruption. Poly-aromatic hydrocarbons also impair the health of other mammals, birds, fish, amphibians, reptiles, invertebrates and plants. Machol and Rizk (2013) estimated that the economic value of air quality caused health impacts resulting from the use of fossil fuels (mainly for electricity generation) in the

US. These estimates include valuation of premature mortality and other health endpoints, workdays lost and direct costs to the healthcare system associated with direct emissions of PM2.5 and of NO_x and SO_2 as PM2.5 precursors. In total, they estimated that the economic value of health impacts from fossil fuel electricity in the United States is between $361.7 and $886.5 billion, annually, representing between 2.5% and 6% of the national GDP, respectively. Their analysis provides evidence that the adverse health impacts of fossil fuels are very significant. Another important finding by Machol and Rizk (2013) is that diesel vehicles with older engines have significant associated adverse health impacts.

Ekener-Petersen *et al.* (2014) evaluated the number of risks per social impact category associated with various types of vehicle fuels (including both fossil fuels and biofuels) and found that high or very high risks of negative social impacts are present for all types of fuels included in their study. The categories most at risk were found to be labour issues, human rights and health and safety, as shown in Figure 2.11.

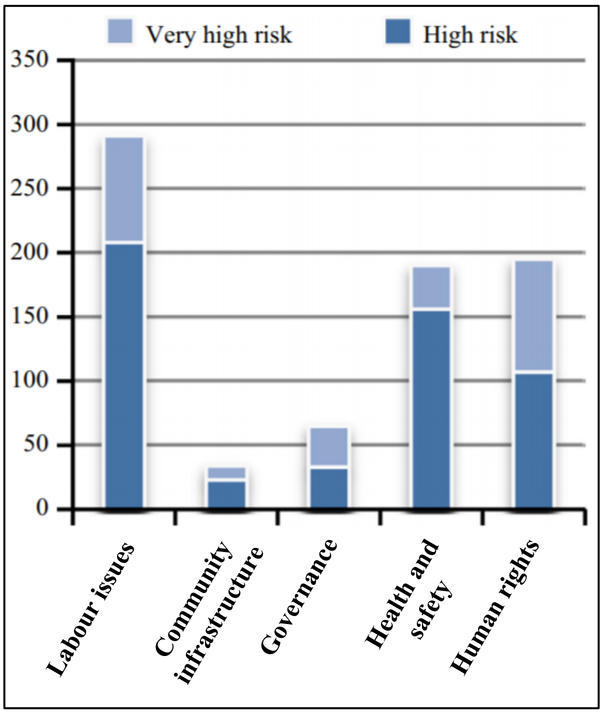


Figure 2.11 Total number of vehicle fuel related risks per social impact category (Ekener-Petersen et al., 2014)

Climate change and global warming poses a significant potential threat to the future economic well-being of large numbers of humans, which will have a knock-on effect in terms of social consequences. Adaptation to change (or failure to adapt) can be slow and costly. Climate change could also undermine social welfare and equity in an unprecedented manner: the response to change and the ability to adapt will not, necessarily, be equivalent across demographic groups, be it geographical or income related (Munasinghe, 2004).

On the other hand, shifting to renewable, clean energy sources might also induce some negative societal impacts: natural landscapes and recreational areas can be lost to electricity utilities (for the development of wind farms or hydro stations, for example), jobs can be lost due to the decline of fossil-based energy provision and people's standard of living can decline if the cost of living rises due to more expensive energy generation. Noise pollution and vibrations, as well as other improvements or deteriorations in the quality of life can, furthermore, occur in the vicinity of renewable energy sources (Stigka *et al*., 2014). Conversely, Akella *et al.* (2009) lists health improvements, greater consumer choice, greater self-reliance, increased work opportunities and technological advances as some of the social benefits of the adoption of renewable energy systems.

In conclusion, it is evident that a fossil fuel dependent freight sector renders dire impacts on social sustainability, irrespective of whether the impacts are generated during the production and supply of fossil fuel-based energy sources or during the consumption and use of fossil-based energy.

2.4 Spotlight on South Africa

The South African surface transport network moves about 1750 million metric tonnes of cargo per annum (Figure 2.12). Cabotage, pipelines and air freight only account for a very small additional amount of freight movement in the country. Road freight enjoys the lion share of surface freight, making up 70.1% of total tonne-kilometres (tkm), and is completely oil driven.

Internationally, the gross value added by road transportation, as a percentage of the gross domestic product (GDP), varies from 0.8% in the United States of America (USA) to 1.6% in Australia. South Africa and the United Kingdom (UK) have similar percentages, with 1.1% and 1.3%, respectively (CSIR Built Environment, 2013). Road transport costs as a percentage of GDP, on the other hand, was the highest in South Africa, at 4.7%, followed by 4.1% in the USA, 3.1% in Australia and 2.5% in the UK. In fact, the contribution of South African transport costs to overall logistics costs was estimated at 58% in 2015 (Figure 2.13). This is significantly higher than the global average.

One of the major reasons for South Africa's relatively high freight transport costs is the fact that South Africa's economic hub, Gauteng, is located inland, far from the nearest port. This is unlike the comparison countries, where the main economic hubs – London, New York and Sydney – are all located closer to ports (CSIR Built Environment, 2013). Additionally, a closer look at the road transport cost constituents indicates the gravity of fuel's contribution to total transport costs being more than double that of the second highest cost element, namely wages. “The vulnerability of transport costs to a volatile exogenous cost driver – the price of crude oil – and South Africa’s entrenched dependence on road transport does not bode well for the economy if the future is to be business-as-usual” (CSIR Built Environment, 2013).

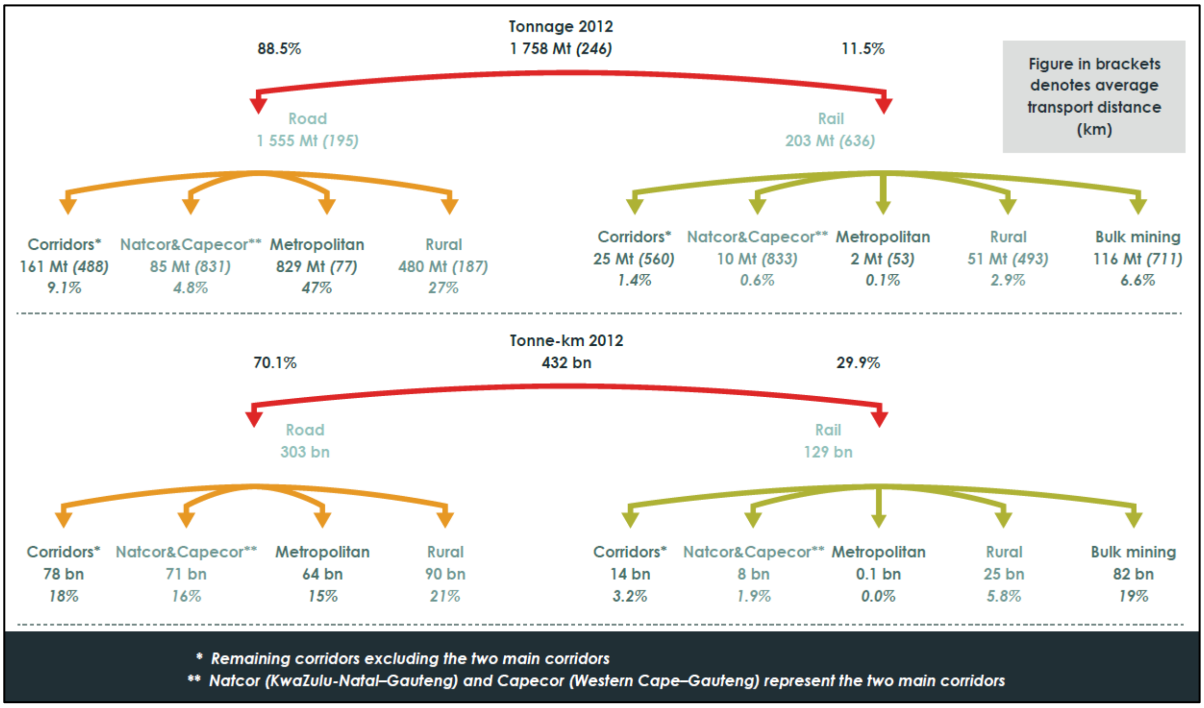


Figure 2.12 South African road and rail freight volumes in 2012 (CSIR Built Environment, 2013)

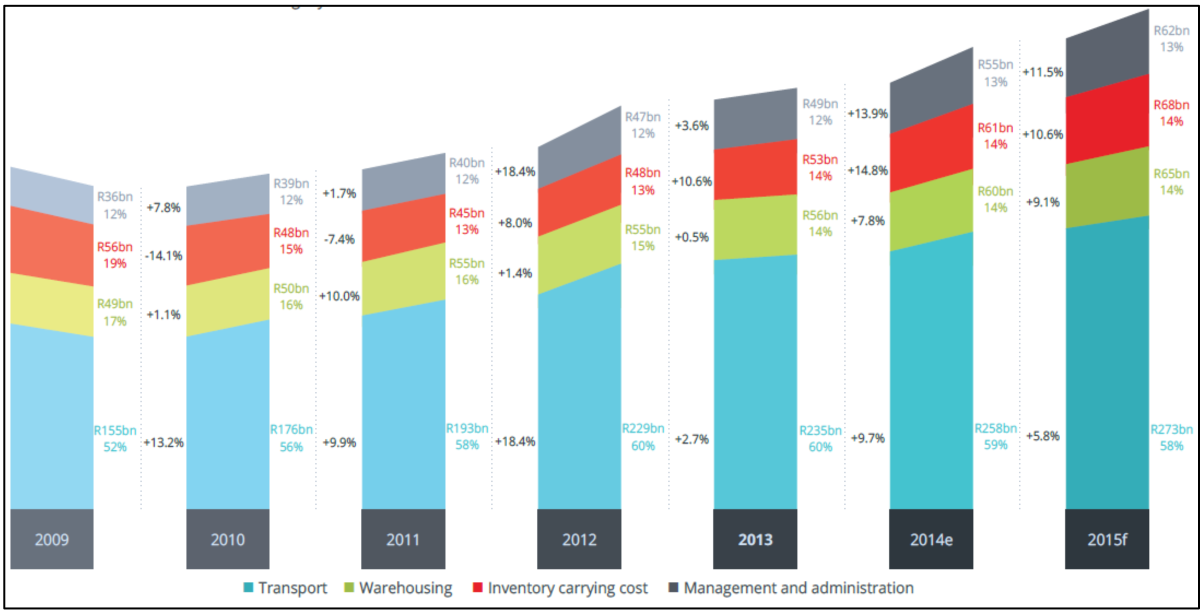


Figure 2.13 Contribution of South African logistics cost components to overall logistics costs (Havenga et al., 2015)

With 70.1% of South Africa's inland tonne-kilometres on road, challenges and cost escalations in the road freight sector affect all South Africans – businesses and consumers alike. Further to this, the South African Department of Transport (2005) proclaimed that: "The freight system in South Africa is fraught with inefficiencies at system and firm levels. There are infrastructure shortfalls and mismatches; the institutional structure of the freight sector is inappropriate and there is a lack of integrated planning. Information gaps and asymmetries abound; the skills base is deficient and the regulatory frameworks are incapable of resolving problems in the industry".

Data gathered from a broad range of industry and government stakeholders in 2013 identified key challenges and cost drivers in the South African road freight sector (CSIR Built Environment, 2013). Respondents felt that poor road conditions (64%), the cost of fuel (52%) and a lack of law enforcement and prevalent non-compliance (43%) are the top three challenges in the industry. In terms of environmental and social impacts, accidents and emissions are the main negative consequences and externality cost drivers of current surface freight movement in the country. This is followed by noise, congestion, land-use and policing (CSIR Built Environment, 2013).

South Africa's energy mix is mostly to blame for the high emissions. The freight transport sector is entirely powered by fossil-based energy: oil (98% of total energy demand) is used for road-, rail-, air- and water-based propulsion and coal-generated electricity (2% of total energy demand) in the rail and pipeline sectors (Figure 2.14). In 2011, South Africa generated 94% of its electricity using coal (IEA, 2013b), rendering transport energy supply 100% fossil fuel-based. South Africa has submitted a pledge, under the Copenhagen Accord, to reduce emissions by 34% by 2020 and by around 42% by 2025, compared to a current emission baseline (IEA, 2013b). Curbing emissions from transport will go a long way towards achieving this goal. The heavy reliance (over 90%) on imported crude oil is a threat to the sustainability of the current South African freight transport system. "This high level of dependence on imported crude oil exposes the economy to potential events that either interrupts supply or leads to higher oil prices, thereby undermining economic growth and development" (Nkomo, 2009).

Efforts to improve the South African freight system's sustainability profile should, thus, be aimed at reducing the total volume of fuel consumed, changing the fuel supply that powers the sector to more sustainable sources, or changing the modal split to modes that can operate using more sustainable energy sources.

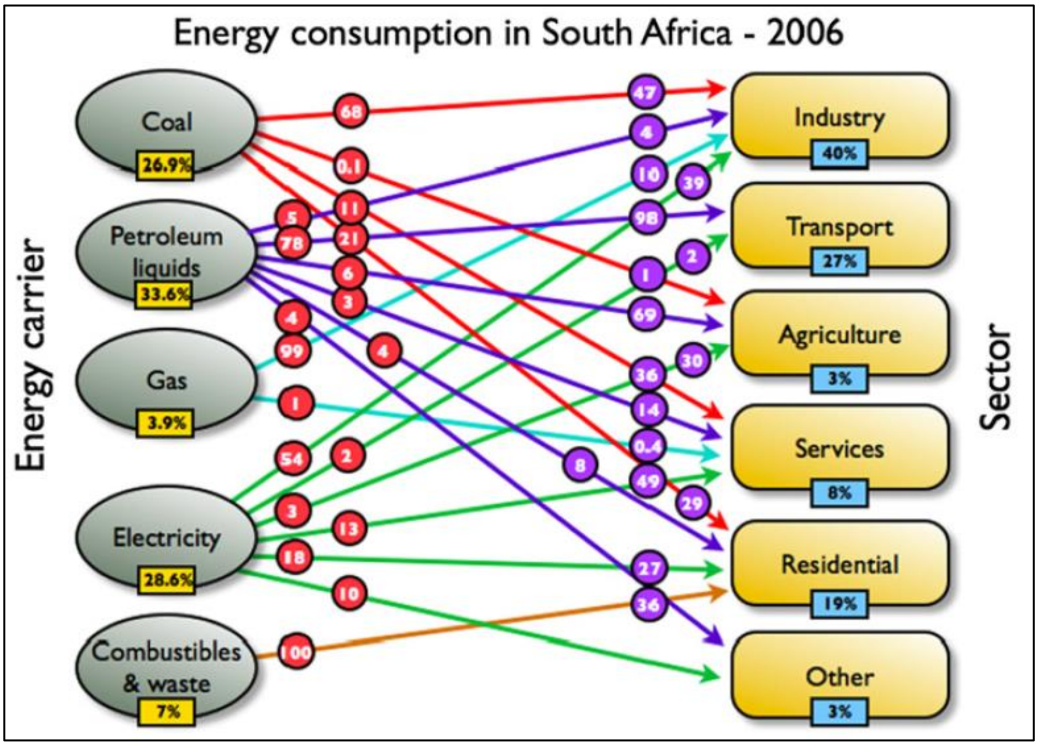


Figure 2.14 Final energy consumption in South Africa (Vanderschuren et al., 2010)

2.5 Chapter Summary

It can be surmised that current and expected future freight transportation operations are (and will continue to be) wholly unsustainable, which is an unacceptable state of affairs. "The simple fact is this: in meeting our needs, we are destroying the ability of future generations to meet theirs" (Hart, 1997). This chapter demonstrated how energy use in freight transport affects all three pillars of sustainability. It can be concluded that the major opportunity for conversion to sustainable freight operations lies within the management of energy use in the sector, thereby answering the research question (1.1) of whether freight energy management will have a significant impact on freight transport sustainability. This is true both for the global freight sector, as well as for South African freight operations. The IEA (2013a) supported this claim when they pronounced that those who anticipate global energy developments successfully can derive an advantage, while those that fail to do so risk making poor policy and investment decisions. Furthermore, they state that awareness of the dynamics underpinning energy markets is essential for decision-makers attempting to reconcile economic, energy and environmental objectives. Implementation of the right combination of policies and technologies is, however, proving that the links between economic growth, energy demand and energy-related CO_2 emissions can be weakened (IEA, 2013a).

3 Problem Formulation

This chapter describes the problem formulation process, which corresponds to steps one and two of the standardised operations research process discussed in Section 1.5 and Appendix B. The critical process of formulating and scoping the problem, identifying the values of interest and the range of alternatives to be considered, is discussed. The work done in this step essentially determines what will be included in, and excluded from, the operations research tool developed. A mathematical formulation of the decision variables, objectives and constraints is then developed, delineating the relationships between these elements. To illustrate this process, the problem formulation of the case study model is discussed in detail throughout the chapter. It should be noted that, as the case study is primarily used as a development and communication tool in this dissertation and there is no client, it was deemed appropriate not to elicit stakeholder participation where the process allows for this. Rather, it can be assumed that the decisions listed are typical examples of the consensus decision reached as the final outcome of stakeholder deliberation.

3.1 Defining the Problem and Scoping the Problem Boundaries

The starting point for development of a decision support tool is to fully understand the intended purpose of the tool and its intended use. This knowledge will shape and guide formulation of the tool. In the context of the research at hand, the goal is to develop a decision support tool for the formulation of freight transport energy management strategies, allowing the development of holistic, sustainable and comprehensive freight management policy by government level decision-makers. This goal definition identifies the intended user of the tool (government level decision-makers), the intended domain of the tool (freight energy management) and the intended purpose of the tool (to formulate holistic, sustainable and comprehensive freight energy management strategies).

As a rule, the broader the scope of an operations research model, the more complex, data, time and resource consuming the model becomes. On the other hand, the solutions generated potentially become more realistic and practicable. There is, thus, a trade-off between the practical scale of the model and the potential quality of the outputs generated. This trade-off can be likened to the trade-off between accuracy and error costs in forecasting, shown in Figure 3.1. Scoping a project is an attempt at defining the levels of accuracy around the optimal range for the problem at hand, which is often quite subjective. Stakeholder input during the scoping phase is essential, providing insight to, and approval of, the relevant acceptable error and accuracy costs.

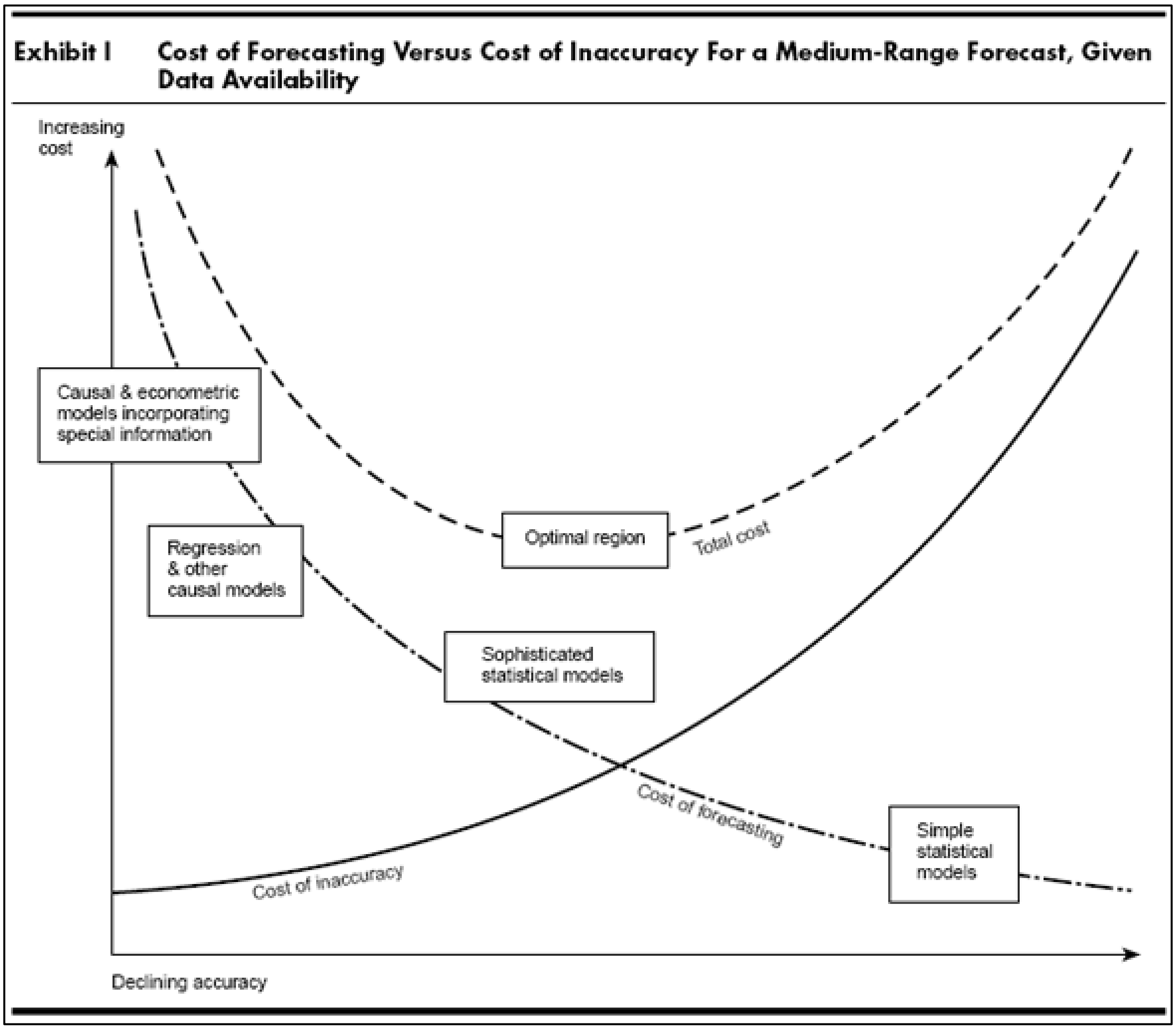


Figure 3.1 Trade-off between cost and accuracy in forecasting models (Chambers et al., 1971)

Prior to commencement of any modelling initiative, it is imperative to have a clear and non-ambiguous idea of what is to be achieved by using the model. Problem scoping is defined as the stage of the design process during which designers explore the relevant issues and set the boundaries of the problem they will continue to solve. During this process, they gather the information they need to clarify or better define a problem, as well as identify the information necessary to formulate a design solution (Atman *et al.*, 2008). It is useful to consider a project from the perspective of several decision contexts, which serve as virtual axes to be used to delimit the project scope. Identification of the decision variables, objective function, constraints and model parameters also form part of problem scoping, subject to the scoping along each decision context.

Four decision contexts are proposed for consideration in development of a freight energy management model, namely: the level of authority of the relevant decision-maker; interaction with systems external to the freight sector; system boundaries of the freight system in question; and timeframe of the analysis.

3.1.1 Decision context one: level of authority of the decision-maker

The questions that guide scoping in this decision context are: who is the decision-maker and what is their purview? Policy measures are implemented on different levels of government administration, implying that different actors and agencies are responsible for various policy measures (Leather and Clean Air Initiative for Asian Cities Center Team, 2009). It is, thus, necessary to know the governance level relevant to the study at hand to enable the filtration of applicable policy measures. Including policies and measures that fall beyond the decision-maker's sphere of influence will not add value and should be eliminated.

In management, there is a certain hierarchy to planning (Figure 3.2). Depending on the level of authority of the decision-maker, the decisions modelled will either be strategic, tactical or operational in nature. If the purpose of the model is to support strategic planning (which in this case it is), promising policies need to be identified at a strategic level, only. A more detailed, lower level, tactical investigation can follow as a secondary analysis (which need only be based on a reduced number of measures to investigate as delimited by a preceding strategic level analysis) if the decision-makers and stakeholders require it. Similarly, should it be required, the favoured measures emanating from the tactical analysis can then be further analysed on a detailed, operational level. The rationale behind this hierarchical and sequential process is to ensure efficiency by not spending a lot of effort on detailed analysis of options that are not deemed strategically viable. Determination of the purpose and planning level of the study is essential in specifying the appropriate level of detail to be modelled, often going hand in hand with the governance level of the decision-maker involved.

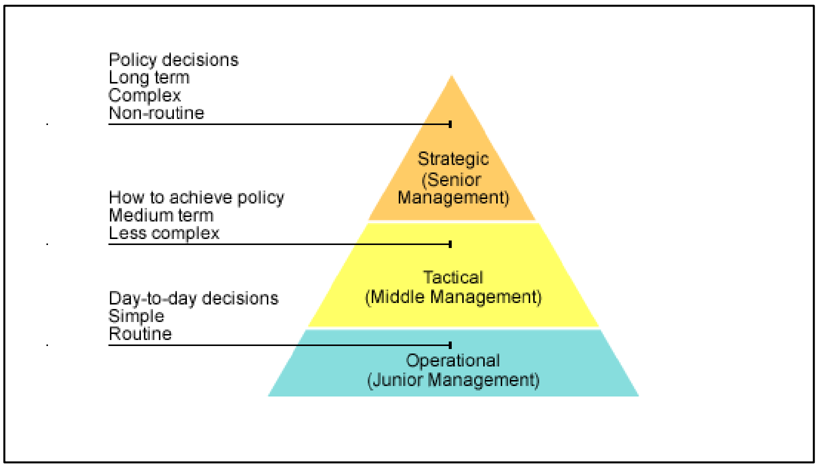


Figure 3.2 Schematic of the planning decision hierarchy (BBC, 2014)

South Africa has a three-tier system of government, with national, provincial and local levels of government who all have legislative and executive authority in their own spheres and are defined in the constitution as distinctive, interdependent and interrelated (Government of South Africa, 2015). The appropriate level of authority, in terms of decision-making targeted in the case study, is national government level policy makers. Accordingly, the analysis is done at a strategic level - only freight energy management measures and policy that can be sensibly implemented on a national scale are included in the analysis.

3.1.2 Decision context two: interaction with external systems

The system to be modelled often forms part of a larger network of systems. It is important to determine within which of these systems the focus of the analysis lies and to what extent the interplay between the system in question and the larger network of systems needs to be reflected in the model. This, as with all the other contextual limitations placed on the analysis, must support the overall purpose of the study.

Freight transportation does not exist, nor does it operate, in isolation. It has a give and take relationship with a country's economy and interacts with various elements of the economy. Figure 3.3 illustrates the network of systems relevant to freight transportation. Economic activity generates demand for goods between producers and consumers, which translates into a physical object needing to be moved from an originating location to a destination at some other location. Freight transportation is the act of physically moving the object between the origin and destination. To do this, equipment - in the form of a vehicle and connecting infrastructure that can be used by the equipment - is required. Some form of energy is required for propulsion of the object and vehicle, necessitating an energy supply network to coincide with the infrastructure network if the energy required to complete the journey cannot be generated or contained on-board the vehicle. All of these components are governed by regulation (of the entire network of systems and within each sub-system).

Although the manufacturing of the required vehicles, the production and supply of the energy sources needed, the construction and maintenance of the necessary infrastructure, the manufacturing or excavation of the goods demanded and the use of the products by the end consumer, all generate sustainability impacts related to freight transportation, it was decided to exclude these external impacts from the case study (as mentioned in Section 1.7). The case study only looks at the impacts emanating from decisions made regarding the physical transportation of the goods in question, subject to the limitations imposed on this freight transportation system (decision context three).

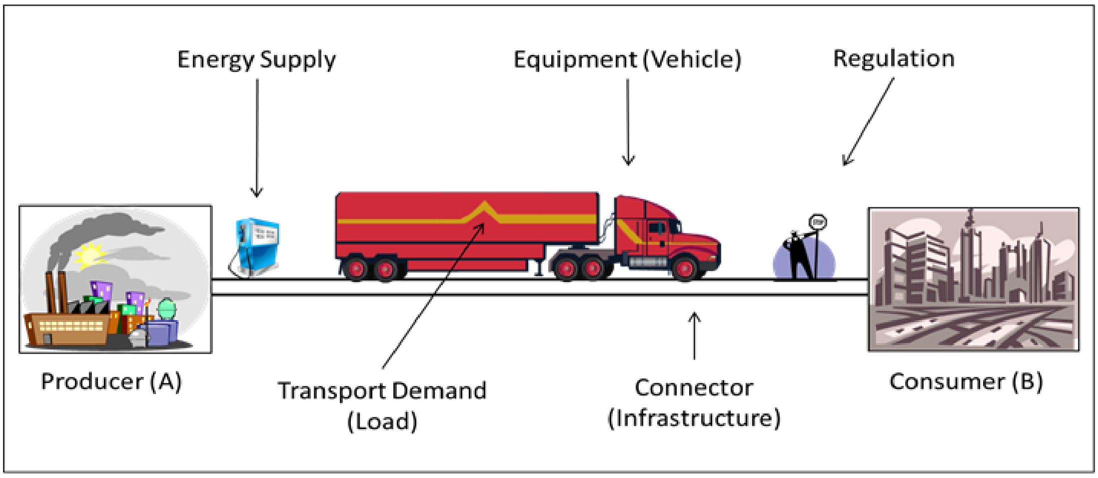


Figure 3.3 Key components of freight transportation

3.1.3 Decision context three: system boundaries

Once it is known which systems and what level of interaction between them will be modelled (decided in decision context two), it is necessary to determine the boundaries imposed on these included systems. As mentioned in Appendix B, a model is a simplified representation of a real-world system. Scoping is required to delineate the boundaries of the real-world system being modelled, as well as that of the actual model. Although freight energy management is a global problem, with global consequences, it is not practical to attempt to address the full global extent of the problem in a single study, for example. Decision-makers need to curtail the system boundaries to such an extent that the model outputs will provide useful decision support within their spheres of influence. Questions pertaining to the level of detail and aggregation in the model, as well as the range of options included in the model, should be answered when scoping within this decision context. Scoping is usually done to determine what the base case model configuration should be to adequately capture the current or default real-world situation. Variations to this configuration will be modelled and explored in subsequent modelling steps.

Relating this to freight transportation modelling, the first question to answer is who the producers and consumers in question are, followed by the question of what needs to be transported between them. This corresponds to the trip generation step of the traditional four-step transport modelling approach, depicted in Figure 3.4. Once the range of goods to be transported has been defined, the allowable set of locations from where the goods are picked up (origins) and the allowable set of locations where they must be delivered (destinations) need to be specified. This, in turn, corresponds to the trip distribution step in the four-step model, which is followed by the modal split step. Here the set of modes that can be considered for inclusion in the analysis is determined. The next course of action is to specify the infrastructure options (connections) available to connect each origin and destination by each mode of transport included. This can be likened to the route assignment step of the four-step model. It is important to note that, while the logic in this scoping exercise follows the same sequence as that of the four-step model, no decisions in terms of modal split, nor route assignment, are made yet. The objective here is simply to define the range of options that the basic model will consider as decision alternatives later on.

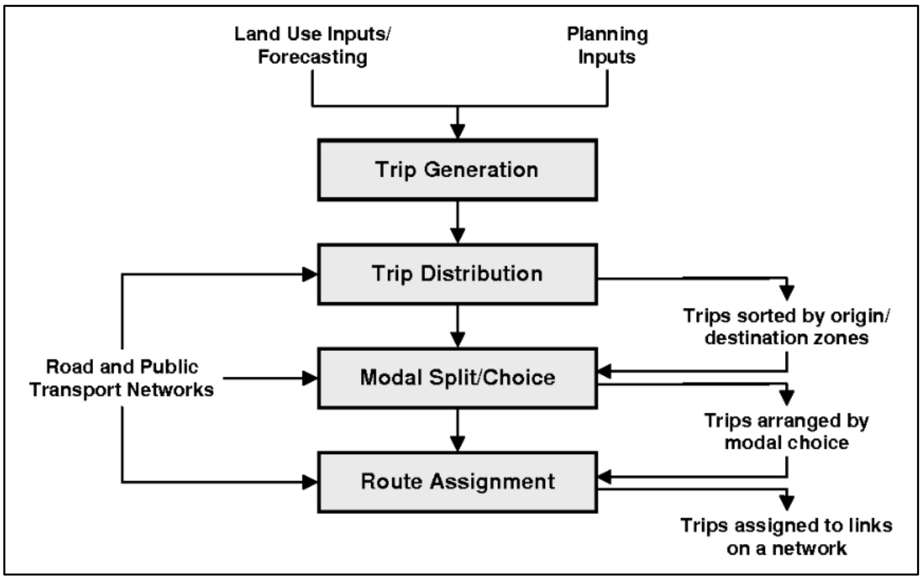


Figure 3.4 The four-step transport model (Evans et al., 2007)

Three more key components of freight transport (Figure 3.3) still need to be addressed in terms of defining system boundaries. The range of equipment (vehicles) allowed to effect transport in each mode needs to be specified. This refers to the type and size of vehicle bodies, as well as the propulsion systems to be considered. Related to the propulsion system specification is the energy supply mix to be included. Finally, it needs to be decided whether there is scoping to be applied based on regulation within the network. An example of this would be a limitation on the energy supply mix and propulsion system options considered, based on regulation with regards to fuel standards.

The rest of this section describes the system boundaries applicable to the case study. For reference purposes, a map of South Africa denoting the provincial boundaries and neighbouring countries (greyed out) is provided in Figure 3.5. Looking at the surface freight flow map for South Africa, shown in Figure 3.6, where the "RAM volumes" displayed represent the rail addressable market, it is clear that Gauteng is the major economic activity centre in the country and that connections between Gauteng and the ports account for the majority of surface freight shipments in South Africa. Stripping away South Africa's two world-class freight export machines (Transnet, 2014), the Sishen to Saldanha heavy haul rail line (used exclusively for iron ore transportation) and the export coal heavy haul line between Mpumalanga and Richard's Bay, it is evident that South Africa's general freight business is predominantly focused on two corridors: the Durban to Gauteng corridor and the Cape to Gauteng corridor (Transnet, 2016a). The Port of Durban is Africa's largest container port and is known as the most active general cargo port in Africa (BusinessTech, 2015). The origin-destination (OD) pair in South Africa with the highest freight transport demand between them is Durban and Gauteng, hence this was chosen as the OD pair to focus on in the case study.

Figure 3.5 Map of South Africa with provincial boundaries and neighbouring countries (Mulabisana et al., 2018)

When defining the freight to be included, it is helpful to reflect on the various freight OD pair classes that exist. Figure 3.7 shows an organisation chart of the OD pair classification system. Freight can either be shipped between countries (international), or within a country (domestic). International freight can further be classified either as freight between neighbouring or nearby countries (regional), or between countries far apart (worldwide). On the domestic freight side, there are shipments between origins and destinations that are far apart (long haul freight), shipments to a node relatively close to the origin (rural freight) and shipments within a node (urban freight). The various freight OD pair classes included in the study will affect the extent of routes to be included and excluded (e.g. international transport routes, or only domestic transport routes). Furthermore, different OD pair classes of freight load the network with traffic in different ways (Table 3.1). Urban domestic freight will only utilise and populate urban freight transportation routes, whilst rural domestic freight could utilise only provincially maintained routes, or could utilise urban routes for some legs of the journey as well. In a similar fashion, long haul and international freight could utilise a combination of urban, provincial and national routes. Van Eeden and Havenga (2010) divided surface freight transport (road and rail freight) into four distinct typologies: primary, corridor, rural and metropolitan. The salient characteristics of each typology are compared in Table 3.2. The primary typology refers to ring-fenced logistics systems that are, by nature, mode-monopolistic with known flows. The competitive surface freight transport market refers to the corridor, metropolitan and rural freight typologies.

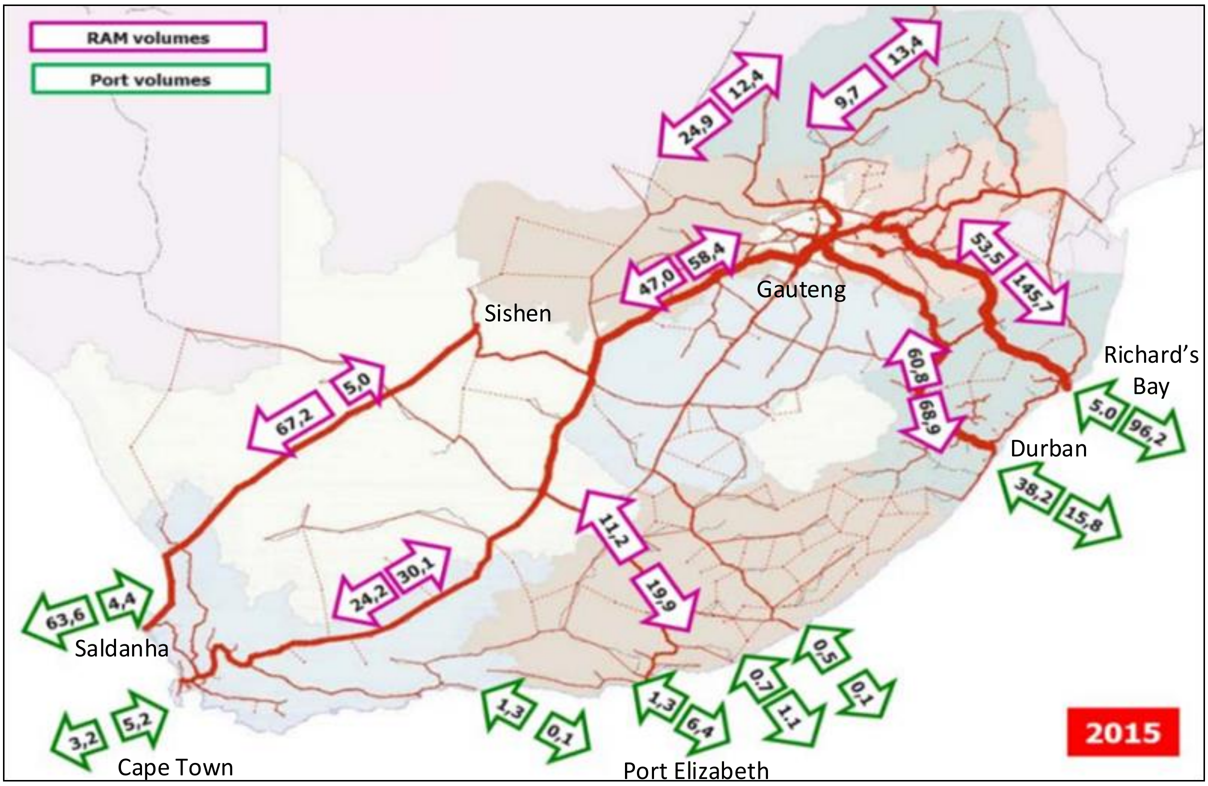


Figure 3.6 Total South African surface freight flows per corridor, port and direction in Mt in 2015 (Transnet, 2016a)

Stakeholders should determine which types of freight routes and which typologies need to be included in the analysis and then indicate which classes of OD pairs will be used to account for freight flow volumes. It is evident that the context decided on regarding the level of authority of the decision-maker will dictate the extent of routes to be considered, with the caveat that higher authority level decision-makers have the option of including more detailed lower level routes in their analyses.

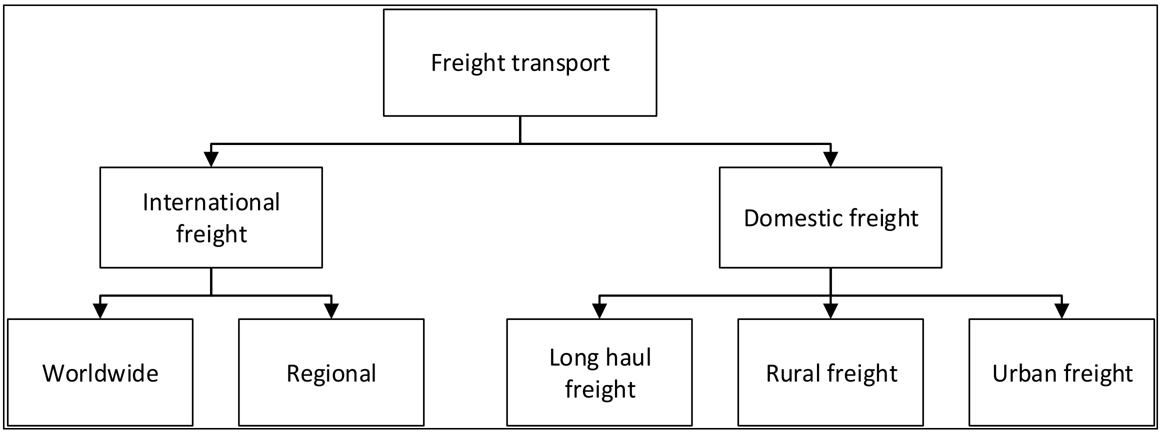


Figure 3.7 Freight transport origin-destination pair classification

Table 3.1 Route loading from different origin-destination pair classes of freight

	International freight	Long haul domestic freight	Rural domestic freight	Urban domestic freight
Urban routes	✓	✓	✓	✓
Provincial routes	✓	✓	✓	
National routes	✓	✓		

Table 3.2 Definition of transport typologies (Havenga, 2013)

Item	**Transport typologies**			
	Primary	**Corridor**	**Rural**	**Metropolitan**
Traffic type	Bulk, low-value (ring-fenced rail-export coal and iron ore; conveyor belt coal; pipelines)	Higher value, mostly manufacturing	Mostly agriculture	Mostly final delivery
Distance	Long and short	Long and short	Medium and short	Short
Origin destination (OD) pairs	Few, usually one-directional	Few long-distance ODs; Many ODs at endpoints	Many	Many
Major challenge	Global competitiveness (export coal and iron ore); energy sustainability	Spatial organisation, efficiency	Development	Congestion alleviation
Ideal logistics approach	Ring-fenced systems	Intermodal solutions	Effective road feeder system	World-class commuter systems and effective freight delivery

The case study includes all freight between the OD pair in question, regardless of whether that is international freight or domestic freight. Urban freight is excluded from the analysis so, for simplicity, Gauteng is modelled as a single node. Both provincial and national routes, as well as rural and corridor typologies, are included.

The commodities to be included in the analysis is an important consideration. Depending on the purpose of the analysis, certain commodities might be excluded from further analysis without loss of consistency and quality in terms of the study outputs. Quite often a lack of adequate data might force analysts to exclude certain commodities from an analysis, or it could constrain the study to an involuntary, higher aggregation level analysis.

Access to reliable, comprehensive and up-to-date freight related data in South Africa, like many other developing countries, is problematic. There is no publicly available freight demand model (although, at present, plans to develop such a system are underway). Some privately developed and owned models do exist, however. The most comprehensive model at present is a national surface freight flow model, owned and developed by Stellenbosch University (Havenga and Pienaar, 2012). Upon request, a limited amount of data from this model was availed for use in this dissertation, hence data availability dictated the commodities to be included in the case study. An origin-destination matrix with surface freight flows (in tonnes) for six commodities was provided for 2011. The six commodities are: processed foods, cement, beverages, industrial chemicals, other chemicals and motor vehicle parts and accessories. These commodities represent the highest volume break bulk surface freight in the country and can be contextualised as follows. The total competitive surface freight transport market in South Africa in 2011 constituted 622 million tonnes, resulting in a transport demand of 178 billion tonne-kilometres (Havenga, 2013). Almost two thirds were delivered over long-distance corridors and one third were delivered in rural areas (not on corridors). Fast moving consumer goods (FMCG), under which processed foods and beverages reside, was the largest source of tonne-kilometres in 2011. Other chemicals, beverages, cement and processed foods are under the top twenty commodities in terms of expected growth in tonnage between 2011 and 2041 (Havenga, 2013). The relative volume of tonnes demanded per commodity is shown in Figure 3.8. The node with the highest sum of total tonnes demanded is Gauteng, followed by Durban (50% of Gauteng's volume) and Cape Town (39% of Gauteng's volume), respectively. These three nodes combined accounted for nearly half of the total tonnes transported in the country.

Although data on air freight, pipelines and cabotage volumes are publicly available from other sources, it cannot be isolated to specific commodities and, therefore, cannot be combined with the rest of the data set. Furthermore, the total volume of freight shipped by these modes are very small when compared to that of surface freight. Despite having this additional data being preferable, it is not detrimental in terms of the case study model purpose and design in this dissertation. According to the data provided for use in the case study (depicted in Figure 3.8), the highest volume commodity transported in South Africa is processed foods. This commodity is also more amenable to shipping with different modes of transport than most of the others provided and it was, therefore, decided to model processed foods flows between Durban and Gauteng in the case study.

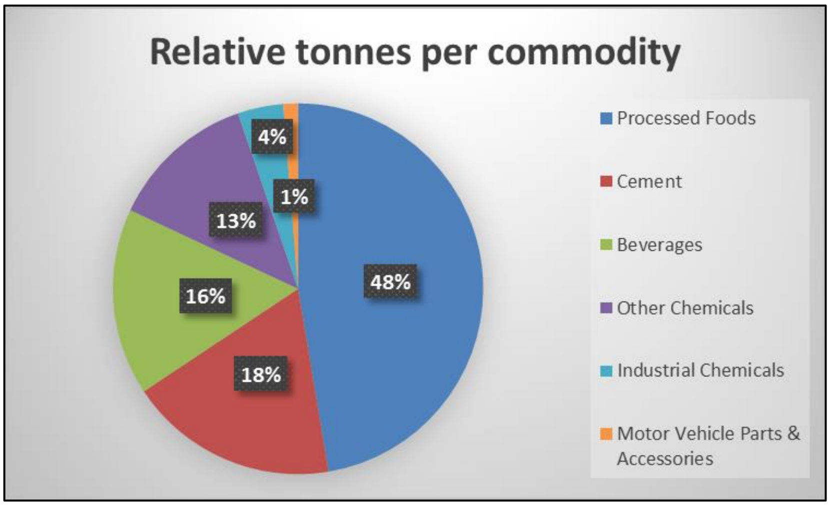


Figure 3.8 Relative demand per commodity (in tonnes) in the case study data

Commodity selection goes hand in hand with modal inclusions and exclusions. Certain commodities dictate the use of specific modes - if they are included in the analysis, the stakeholders will have to consider the modes suitable to, and required for, their transport (for example with breakbulk commodities). The converse also holds true – if some modes are excluded, some commodities might need to be excluded from the analysis. Decision-makers, thus, also have to specify which modes of freight transportation will be modelled, and which excluded, as part of this scoping phase. Four modes, all suitable for the shipment of processed foods, are presently viable options for freight transport in the study area and were included in the case study. These are: road, rail, air and water-based cabotage. Pipelines were excluded due to its incompatibility with the commodity in question. Air freight is typically reserved for lightweight, high value commodities (Popescu *et al.*, 2010), although, in some instances, urgency can dictate the inclusion of a small number of heavy or low value commodities on air cargo manifests. The automotive industry frequently makes use of air freight for transporting spare parts and semi-fabricates of the automotive industry for cars, trucks, motorcycles, etc. (e.g. car seats, engine parts and frame parts) (van de Reyd and Wouters, 2005). Chemicals (e.g. industrial chemicals, adhesives and paint) is another commodity category often shipped via air.

Additionally, processed foods and beverages are also sometimes shipped as air cargo (van de Reyd and Wouters, 2005).

Now that the commodities and modes for inclusion have been determined, a route network needs to be established for each mode. These networks comprise all the viable route segments that can be utilised to transport the freight between the OD pair in question with each mode. South Africa has the tenth largest road network in the world (Wheels24, 2017), spanning approximately 535 000 km (SANRAL, 2018). The case study road network includes 59 road segments connecting 30 nodes, as shown in Figure 3.9.

Similar to road transport, an extensive rail network exists in South Africa spanning more than 22 000 km (Department of Transport, 2017). In the case study, 26 railway links connect the nodes, as shown in Figure 3.10. The route network of the remaining two modes, air and water, is shown in Figure 3.11. Please note that the rail, air and water links on the maps are symbolic and do not indicate the physical pathways of the transportation lines represented.

The range of vehicles included per transport mode needs to be determined. For road transport, determining the vehicle classes of interest can help to delimit the number of options. The United States Environmental Protection Agency (US EPA) uses a classification system based on the gross vehicle weight rating (GVWR) to distinguish between different road freight classes (US EPA, 2012). In the South African freight databank, vehicles are classified according to the number of axles per vehicle (Table 3.3). It is widely accepted that LDVs are not used for long distance freight transportation, but rather in the urban freight environment, therefore, vehicle groups two to six in the South African classification are used. For each vehicle group, four different vehicle body types (tautliner, cattle carrier, tipper and tanker) were initially included to account for the potential transportation needs of different commodities. There are, thus, 20 different road vehicle types included in the case study vehicle park. Each of these trucks are deemed compatible with either a standard internal combustion engine (ICE) or a hybrid-electric engine for its propulsion system. Internal combustion engines can use either regular diesel or biodiesel and the hybrid-electric engines only regular diesel.

For rail transport, both locomotive and wagon types need to be specified. There are seven locomotive types (Locomotives of South Africa, 2018) and four wagon types (Kritzinger, 2013) included in the case study, named according to the names of the rolling stock used in South Africa. This encompasses four electric locomotives (classes 10E, 18E, 14E and Exp AC), one diesel-electric locomotive (class 38-000) and two diesel locomotives (classes 43-000 and 36-000). Not all locomotives can be used on any piece of rail track. Railway track sections are classified according to the types of locomotives that can use

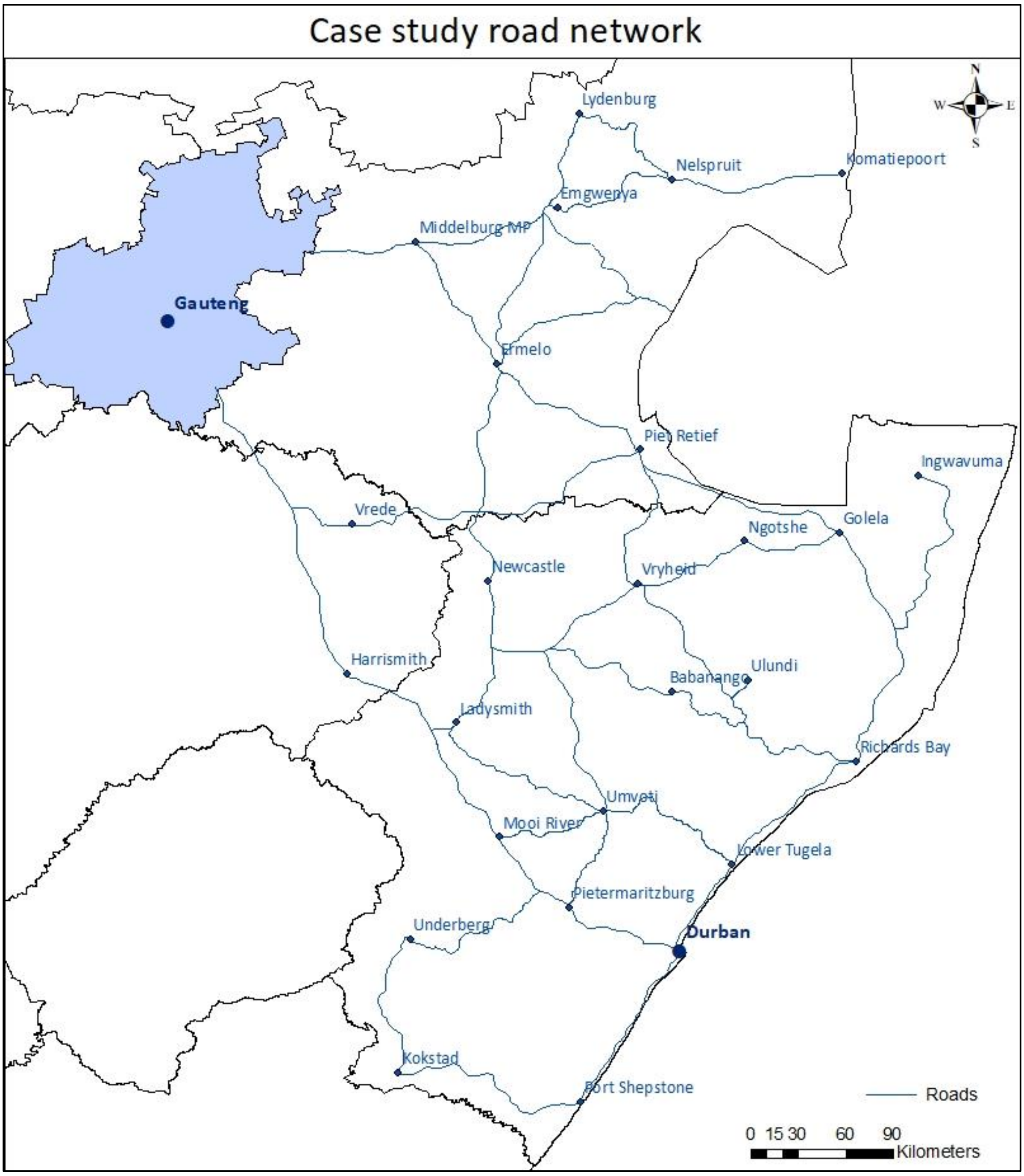


Figure 3.9 Case study road network and nodes

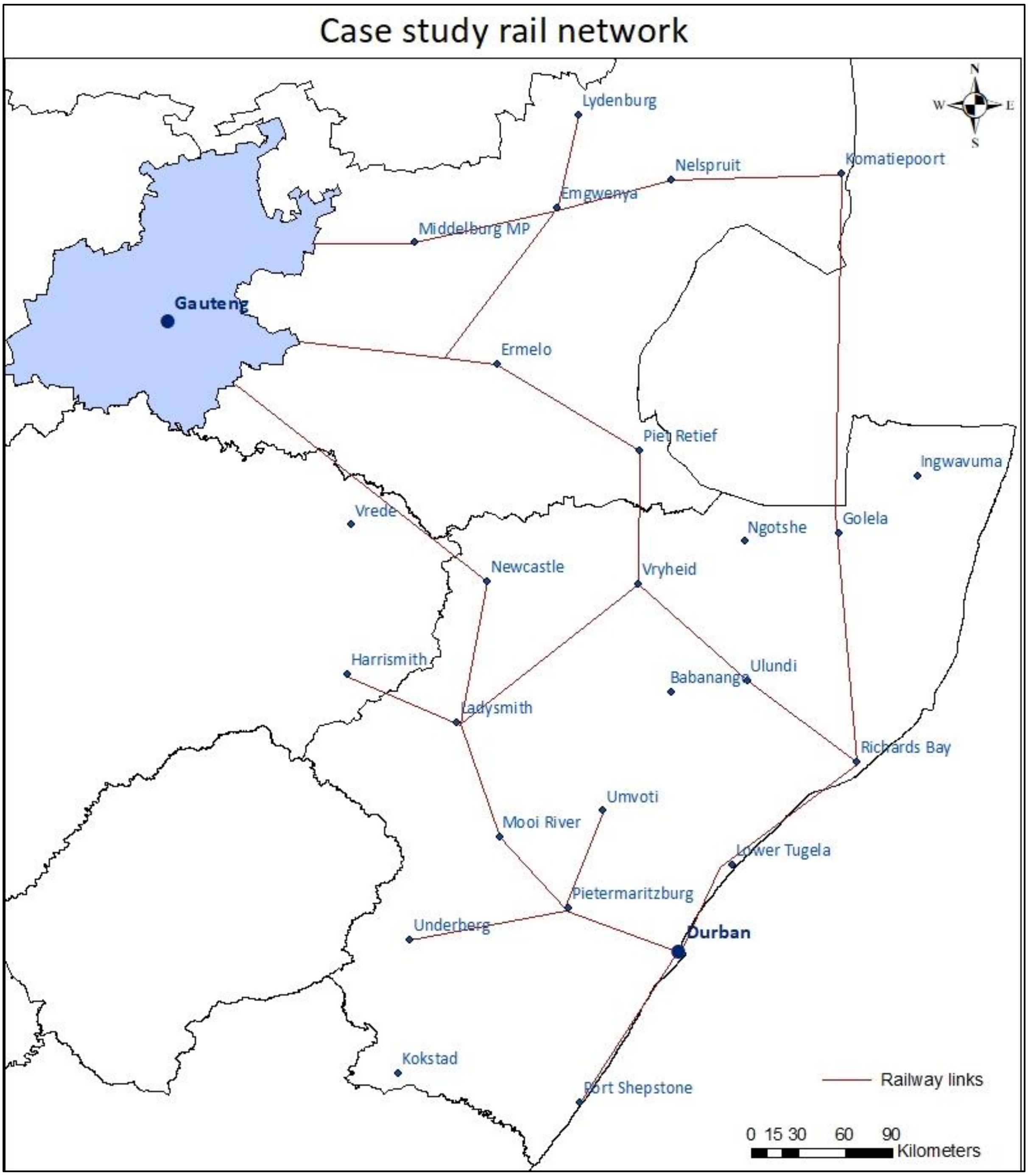


Figure 3.10 Case study rail network

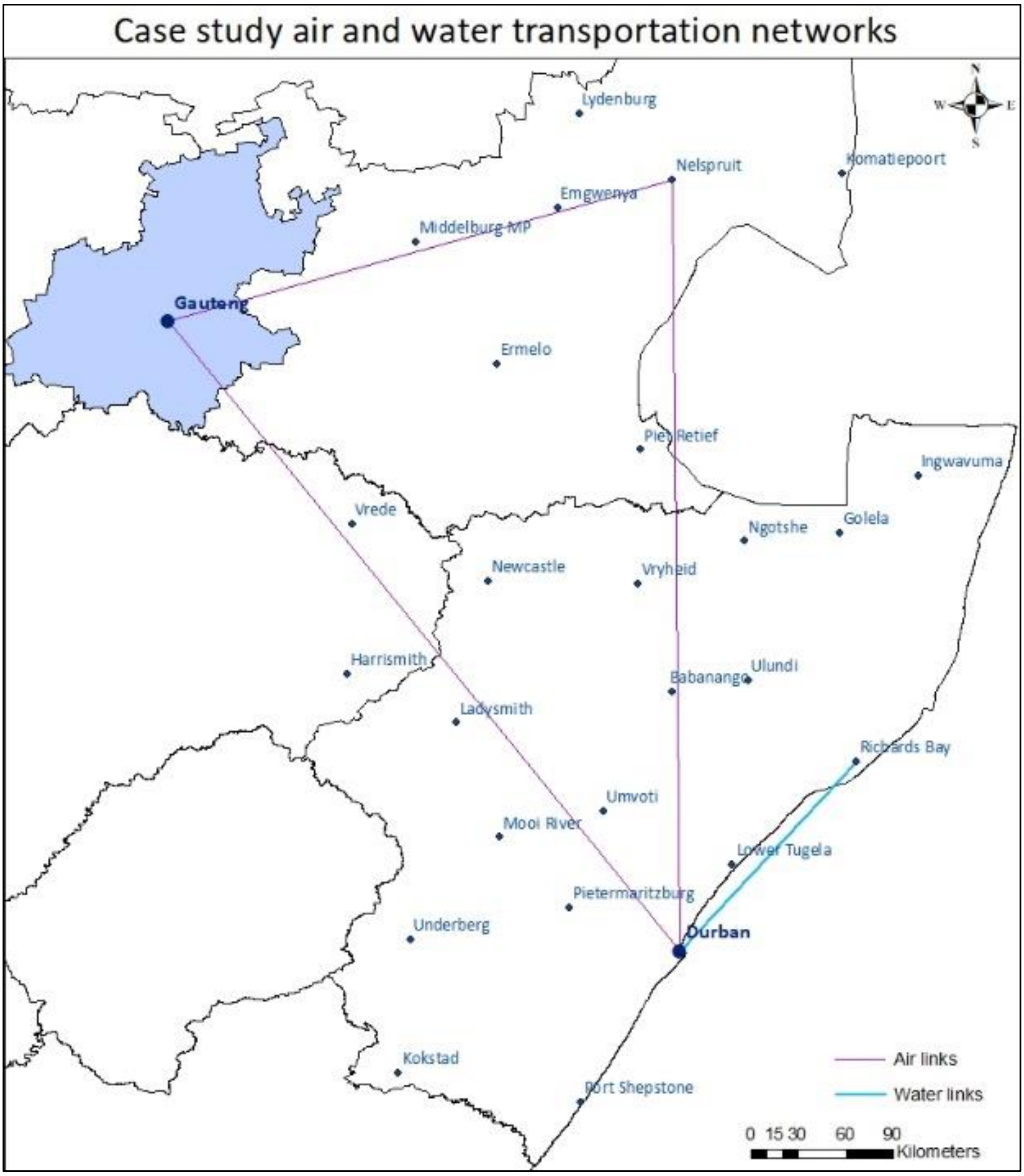
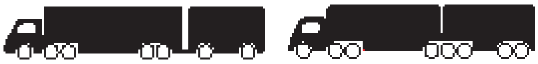


Figure 3.11 Case study air and water transportation networks

Table 3.3 South African freight vehicle classification (Thuysbaert, 2008)

Vehicle Group	Description	No. of Axles	Graphical Illustration
1	LDV – Light delivery vehicles	2	
2	Rigid trucks	2 - 3	
3	4x2 truck tractor and 2 axle semi-trailer	4	
4	6x4 truck tractor and 2 axle semi-trailer	5	
5	6x4 truck tractor and 3 axle semi-trailer	6	
6	Interlink or drawbar	7 - 9	

the specified piece of track. Tracks are classified as either 3 kV DC, 25 kV AC, a mix between these two electrification types and non-electrified. Figure 3.12 maps out the various track types in use in the rail network, while the locomotive track type pairing used in the case study is shown in Table 3.4. The wagons included are FB-1, O-1, XO-1 (a tanker wagon) and DKJ-2. Only the O-1 wagons are compatible with processed foods and the other wagon types are excluded from further analysis.

The relevant definition of freight transport adopted for the specific analysis is another aspect of the decision context of freight systems boundaries and exclusions. While it is understood that freight transport is the physical process of transporting commodities, merchandise goods and cargo - in short, the transportation of anything other than people - there is a grey area where goods are transported along with people, or where goods are transported utilising vehicles normally used for passenger transport (i.e. where the volume of goods transported is relatively small). Definitive resolutions regarding these grey areas need to be taken by the stakeholders. Air freight is transported in one of three vehicles in the case study: a Boeing 737 200 cargo plane, a Boeing 737 300 cargo plane or in the

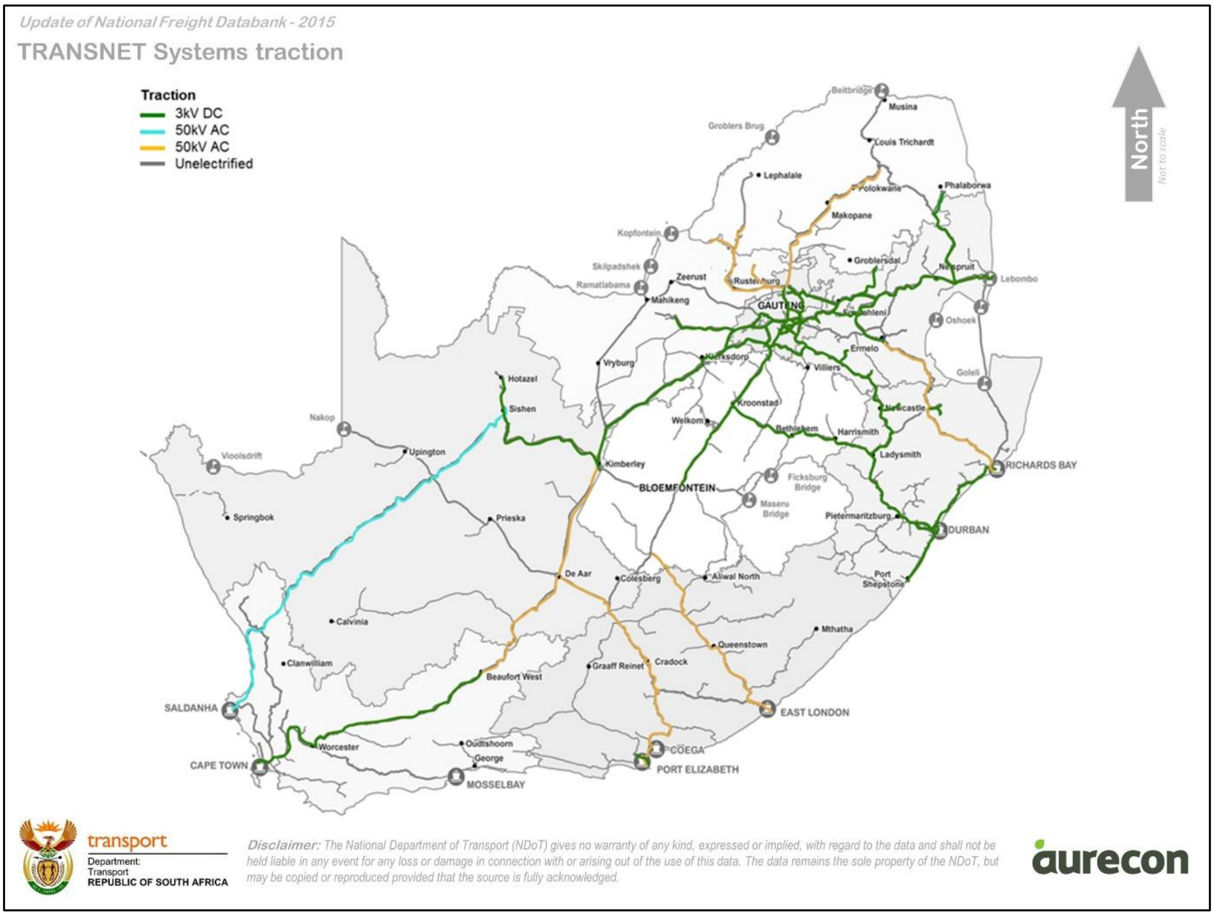


Figure 3.12 Rail network track classification - National Freight Databank of South Africa (http://freightdatabank.info)

Table 3.4 Locomotive pairing to rail track type

	Locomotive type						
Rail track type	**Electric locomotive: Class 10E**	**Electric locomotive: Class 18E**	**Electric locomotive: Class 14E**	**Electric locomotive: South African Class Exp AC**	**Electro-diesel locomotive: Class 38-000**	**Diesel locomotive: Class 43-000 (new C30Aci model from GE)**	**Diesel locomotive: Class 36-000**
Diesel (non-electrified)	×	×	×	×	✓	✓	✓
3 kV DC	✓	✓	✓	×	✓	✓	✓
25 kV AC	×	×	✓	✓	✓	✓	✓
Electrified (mix)	×	×	✓	×	✓	✓	✓

hold of a Boeing 737 300 passenger aircraft, however, only the two cargo planes are considered compatible with transporting processed foods. Both aircraft are powered by jet engines.

For cabotage, feeder cargo ships with a 2000 TEU capacity and tankers are considered, powered by diesel ICEs. Because processed foods is the only commodity in question, tankers can be eliminated for the remainder of the study.

Consequent to the vehicle type and propulsion system specification, five energy sources are considered in this study, namely: regular diesel, biodiesel, electricity (generated externally and not on board), jet fuel and bunker fuel (low grade diesel). Air freight (jet engines) is the only user of jet fuel. Similarly, water freight transport is the only user of bunker fuel. Regulation was not an explicit scoping factor in the case study.

3.1.4 Decision context four: timeframe of the analysis

Analyses can either be classified as static, or dynamic. In static analyses, a snapshot view of the situation is modelled and all model elements are considered at their respective values during the same moment in time. The variables and parameters in a static model do not evolve over time. It is, however, possible to consider future development profiles statically through discounting approaches, if this is deemed necessary. In dynamic analyses, the evolution of the various elements happens simultaneously and the combined impact of such evolutions inform the next evolution in the next time step. A timeframe needs to be specified for the analysis and the analysis takes on an iterative structure. It is essential for decision-makers to understand the difference between these two approaches, before they can select the most appropriate methodology for the problem at hand. This choice has far reaching consequences for the type, structure and data requirements of the analysis to follow.

The freight demand data available for use in the case study sums the total freight demand over one year, thus providing a snapshot view of flows in the network. The purpose of the model is to identify the optimal combination of freight energy management measures to be applied in the network. This can be done with either a static or dynamic approach. Given data and resource constraints, a static approach was followed. The impacts of measures applied are valued at their peak levels; implementation and cooling down periods are excluded from the analysis. The most promising measure combinations identified by this model can be used as input into a dynamic model of reduced scale to provide decision-makers with more information, should the situation allow for or require this.

3.2 Identification of the Decision Variables

Decision variables represent the interventions that decision-makers can use to manipulate the system in question. For government level strategic analysis, this is normally restricted to policy making. Decision variables typically identify which policies to implement and in what way. As a start, the range of decision variables to be considered by the model needs to be defined. It is good practice to start with a list of all the potential options under consideration, filtering them step-by-step until the smallest number of options that the decision-makers cannot make further judgement over are left. Scoping the problem boundaries is often the first filter to be applied - all variables to be included are implicitly subject to the scoping decisions made in Section 3.1. The next filter is subjective preferences for inclusions and exclusions expressed by the stakeholders. Finally, logic filters in terms of data availability or model consistency can physically limit the options further. It is important to not pre-evaluate and judge measures as part of the filtration process – the ideal is to let the model decide unbiasedly. Therefore, best practice is to rather include more decision variables if one is unsure, to allow enough freedom so that the model is not predictable.

A literature review on freight transport energy management measures (summarised in Section 1.1 and Appendix A) shows that there is such an abundance of measures available to policy makers, filtration becomes a necessity. Decisions impacting the final energy consumption of the freight sector are made by two key role-players. The first is government, which creates policies shaping the world within which the second role-player, the logistics sector, operate. Decisions made by logistics managers have a direct impact on energy demand, but these decisions must be made within the boundaries set through policy.

As mentioned, only measures that can be implemented by the relevant decision-makers in a specific decision context need to be considered. All measures that fall beyond the scope of the study at hand should be excluded from further analysis, hence only strategic level freight energy management measures are to be considered in the case study. From a government perspective, both policies and operational measures exist as levers to manage freight transport energy demand and these can all be seen as potential decision variables. Table 3.5 displays the reduced list of government level freight energy management measures considered for inclusion in the case study (denoted GM). The impacts of these measures on freight energy consumption are highlighted and examples of said measures provided in each of the tables.

Good freight policies can only be developed with the needs of the logistics sector in mind, therefore, information on what the ideal logistics management practice would look like is incredibly valuable in developing policy and setting of policy targets. For this reason, the case study will also look at operational instruments that can affect freight energy management. If the ideal operational network configuration is known, decision and policy makers can tailor policy to support the realisation of this configuration, or at least remove barriers to entry. Table 3.6 lists the logistics sector level operational instruments considered for inclusion in the case study (denoted LM). An indication of the policies that influence each instrument, as well as the instrument's impact on freight energy consumption and

Table 3.5 Government level policy and operational measures considered for inclusion in the case study

Freight energy management measure category	Government level policy measures	Impact on freight energy consumption	Examples
Planning instruments	Network infrastructure planning and development	Freight network design influences freight operator decisions on modal split and routing (ultimately affecting travel distances and time per mode). This also influences the availability of intermodal and intramodal transport facilities in a network.	Opening a new port; closure of certain roads for certain heavy vehicle classes; adding intermodal transfer facilities to the network.
	Energy sector planning and development	The energy supply mix affects modal split, as well as vehicle and propulsion system selection. This ultimately has an impact on the average energy efficiency of transport. Properties of the energy supplied will necessarily be transferred to the transport sector (such as emissions).	Allowing biofuels in a country; halting oil imports.
Regulatory instruments	Vehicle park restrictions	Affects the number of vehicles of each configuration in use, ultimately affecting average energy consumption per tkm.	Restrictions on allowable vehicle size, weight, age before retirement, engine size, engine types (e.g. banning ICE vehicles).
	Energy supply quality restrictions (i.e. fuel standards)	Affects overall propulsion efficiency.	Restrictions on the fuel types to be sold in a country.
	Operational regulation	Changing the operational parameters in the network will affect transport times and the number of trips required, which could impact modal split and vehicle and route selection.	Regulation with regards to operational parameters (e.g. speed limits; overloading; vehicle maintenance levels).
Economic instruments	Taxes	Taxation structures designed to promote energy efficiency through tax benefits or penalties for non-achievement of the tax objectives can affect overall energy consumption of the network by affecting decisions made on mode and vehicles to be used by transport operators.	Energy taxes; vehicle taxes.
	Subsidies	Subsidies can skew development trends in the freight sector towards more energy efficient modes and propulsion systems, or greener fuel sources.	To promote specific technologies (such as electric vehicles).
	Rebates	Rebates can incentivise role-players in the feight sector to adopt more efficient and cleaner technology sooner than it would happen organically.	For scrapping of elderly propulsion systems and out-dated technology, to be used for upgrading to modern technology.
	Infrastructure pricing (per mode)	Infrastructure pricing can be used to influence modal choice, as well as route selection.	Toll roads; harbour and airport taxes; direct charge zones.
Educational instruments	Training of transport operators	Training of transport operators will result in improvments in overall energy demand in the freight network.	Driver behaviour training; basic awareness of factors that affect energy consumption (e.g. tyre inflation and size, air-conditioning system use).
Research and development instruments	Development of new technology and research on existing technology	New, groundbreaking technologies (such as autonomous driving systems, the Hyperloop, alternative fuels and propulsion systems and 3-D printing) can dramatically alter the composition and operation of the freight sector. Continued research on existing designs can lead to efficiency improvements resultant from design improvements.	Policies to enable the adoption and integration of new systems into the current system.
Freight energy management measure category	**Operational measures on a government level**	**Impact on freight energy consumption**	**Examples**
Enforcement of instruments	Tolerance for non-compliance and levels of law enforcement	Lower tolerance will see greater achievement in terms of intended consequences.	Enforcing compliance with overloading regulation or speed limits.
Maintenance	Levels of maintenance of freight network infrastructure	Poor infrastructure can result in avoidable excess energy consumption due to poorer fuel efficiencies achieved and different route or modal choices that result.	Potholes lead to stop-start driving which consumes excess fuel; taking longer roads to bypass sections with potholes.
Research and development instruments	Development of new technology and research on existing technology	New, groundbreaking technologies (such as autonomous driving systems, the Hyperloop, alternative fuels and propulsion systems and 3-D printing) can dramatically alter the composition and operation of the freight sector. Continued research on existing designs can lead to efficiency improvements from design improvements.	Promoting and enabling research and development on promising technologies in the freight transport sector.

Table 3.6 Logistics sector operational instruments considered for inclusion in the case study

Logistics sector operational instrument	**Impact on policy development or government operations**	**Impact on freight energy consumption**	**Examples**
Use of intermodal transport	Network infrastructure planning and development	Consolidation of goods into bulk modes with greater energy efficiency can be done when intermodal connections are viable.	Ro-ro trains; cross-modal interchange infrastructure
Use of intramodal transport	Network infrastructure planning and development; vehicle park restrictions; operational regulation	Consolidation of goods into larger vehicles with greater energy efficiency can be done when intramodal connections are viable.	Distribution centres; hub-and-spoke networks
Modal choice	Network infrastructure planning and development; vehicle park restrictions; operational regulation; infrastructure pricing; law enforcement	Different modes have different energy efficiencies and a change in modal split will yield a change in overall energy consumption.	Shifting from road to rail
Route selection	Network infrastructure planning and development; operational restrictions; infrastructure pricing; law enforcement	Route selection will affect overall tkms, ultimately affecting total energy demand.	Taking longer, rural roads to avoid highway tolls
Vehicle selection	Vehicle park restrictions; energy supply quality restrictions; operational regulation; taxes; subsidies; rebates; infrastructure pricing	Different vehicles have different energy efficiencies and a change in vehicle split will yield a change in overall energy consumption.	Using Interlinks versus a fleet of rigid trucks
Vehicle loading regimes	Vehicle park restrictions; operational regulation; infrastructure pricing; law enforcement	Vehicle loading regimes impact total tkms, which affects overall energy consumption.	Load consolidation; minimum load acceptance policy
Propulsion system selection	Energy sector planning and development; vehicle park restrictions; energy supply quality restrictions; taxes; subsidies; rebates	Different propulsion systems have different energy efficiencies and a change in propulsion system use will yield a change in overall energy consumption.	Using ICE versus hybrid-electric versus full electric trucks
Energy selection	Energy sector planning and development; vehicle park restrictions; energy supply quality restrictions; taxes; subsidies	Different fuels have different energy efficiencies and a change in fuel use will yield a change in overall energy consumption.	Using biodiesel versus low grade diesel versus low emissions diesel
Deliberate energy efficiency improvements	Development of new technology or research on existing technology; training of transport operators; operational regulation	Adopting energy efficiency improvements will result in lower overall energy consumption.	Always operating at the right tyre pressure; no unnecessary idling

examples of each instrument is provided in the table. The case study model will, thus, find the optimal combination of both government and logistics sector policy and operational instruments, simultaneously.

To illustrate that the inclusion of virtually any type of measure is possible in the decision support tool developed, it was decided to select a set of example measures (decision variables) that are

Table 3.7 Decision variables included in the case study model

Freight energy management measure category	**Measure**	**Model implementation**	**Case study decision variable name**
Planning instruments	Network infrastructure planning and development	Alternative network design uploaded	GM1
	Energy sector planning and development	Change energy source options available	
Regulatory instruments	Vehicle park restrictions	Change vehicle options available	GM2
	Energy supply quality restrictions (i.e. fuel standards)	Change available energy source properties	
	Operational regulation	Change the allowable range of operational parameters	
Economic instruments	Taxes	Change formula or parameters for assessing the cost of freight transport	GM3
	Subsidies	Change formula or parameters for assessing the cost of freight transport	
	Rebates	Change formula or parameters for assessing the cost of freight transport	
	Infrastructure pricing (per mode)	Change formula or parameters for assessing the cost of freight transport	
Educational instruments	Training of transport operators	Change formula or parameters for assessing the energy demand from freight transport	GM4
Research and development instruments	Development of new technology and research on existing technology	Change technology options available (mode, vehicles, propulsion systems or energy sources)	GM5
Government operations	Tolerance for non-compliance and levels of law enforcement	Change the allowable range of operational parameters	GM6
	Levels of maintenance of freight network infrastructure	Change formula or parameters for assessing the assorted impacts of freight transport	
	Development of new technology and research on existing technology	Change technology options available (mode, vehicles, propulsion systems or energy sources)	
Logistics operations	Use of intermodal transport	In every simulation the model chooses what freight to transport using intermodal transport	LM1
	Use of intramodal transport	In every simulation the model chooses what freight to transport using intramodal transport	LM2
	Modal choice	In every simulation the model chooses what freight to transport with each available mode	LM3
	Route selection	In every simulation the model chooses what route to use to transport the freight	LM4
	Vehicle selection	In every simulation the model chooses what freight to transport using each avaiable vehicle type for every mode	LM5
	Vehicle loading regimes	In every simulation the model randomly assigns a normally distributed loading capacity uitlisation level per vehicle type and mode	LM6
	Propulsion system selection	In every simulation the model chooses what freight to transport using each available propulsion system for each vehicle type and mode	LM7
	Energy selection	In every simulation the model chooses what freight to transport using each available energy source for each propulsion system	LM8
	Deliberate energy efficiency improvements	Change formula or parameters for assessing the energy demand from freight transport	

representative across the spectrum – one variable representing each government level measure category and each logistics sector operational instrument were included in the case study. Table 3.7 indicates the decision variables included (shaded blue), their model implementation methodology and names used in the case study. Deliberate energy efficiency improvements by the logistics sector were excluded from the analysis, because the model implementation methodology is similar to that of GM4 (training of transport operators) and its inclusion would, thus, not showcase additional tool capabilities. In a real-world application of the tool, multiple variables of each category, or of similar implementation methodologies, will likely be included in the analysis. The case study models six government level measures and eight logistics sector instruments, resulting in a total of fourteen decision variables. Each of these variables are discussed in more detail in the remainder of this section.

3.2.1 GM1: Network design

Changes to the network design can have large ramifications in terms of the transport allocation within a network and, consequently, the sustainability impacts of that allocation. Two alternative network designs are considered in the case study. The basic network design (network one) mimics the status quo of the South African transport network, as discussed in Section 3.1.3. An alternative network design (network two) is provided and the decision on which of the two network designs is used in a solution is represented by the value of decision variable GM1. GM1 is, thus, an integer variable with two possible values, one or two ($GM1 \in [1,2]$).

Transnet's proposed rail upgrades for a heavy haul general freight line linking South Africa and Swaziland is included as part of the rail network in network two. The link, spanning 575 km in total (Figure 3.13), would provide an alternative route to the ports of Maputo and Richards Bay (Luhanga, 2017) and will remove nearly all general freight from the coal export line, freeing up 200 wagon slots for export coal. This will result in a dedicated General Freight Business Corridor for Transnet, while providing necessary additional capacity for Swaziland Railway (Asefovitz, 2017). The line has been designed to carry trains with 150 general freight business wagons, accommodating up to 26 tonnes per axle and will operate seamlessly without stopping at the border. It is planned that the line will have diesel traction, utilising Class 43 diesel electric locomotives (or similar) (GEZSA, 2013; Aurecon, 2014).

Opening the line entails construction of 150 km of new greenfield railway between Lothair (South Africa) and Sidvokodvo (Swaziland) and revamping two existing Transnet lines – from Ermelo to Lothair and from Sidvokodvo to Richards Bay. It is estimated that R20 billion will have to be secured in funding for this project, which can create 3 000 direct construction jobs in South Africa and 6 500 in Swaziland

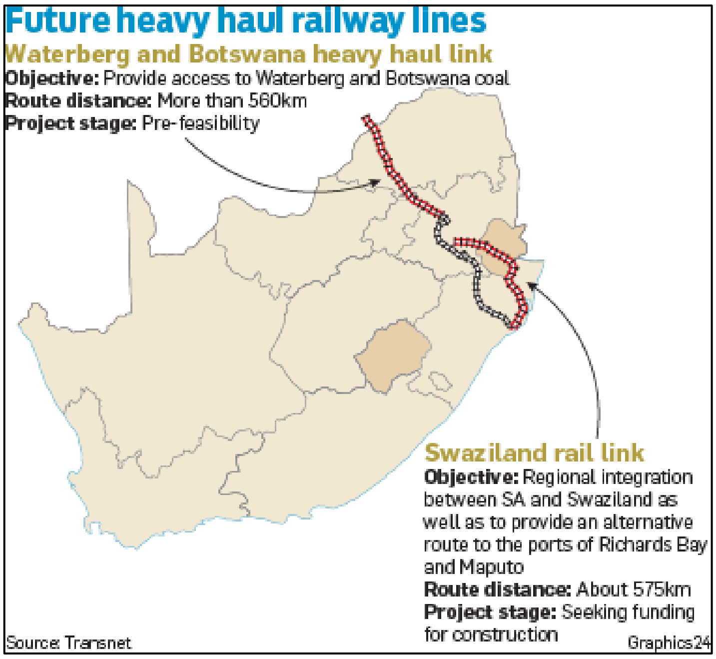


Figure 3.13 Map of future Transnet heavy haul lines (Luhanga, 2017)

(Creamer, 2017). This equates to 1.47 billion US dollars at an exchange rate of R13.6/$. The long-term employment impact arising from train operations and maintenance is expected to be 500 jobs in South Africa and 300 in Swaziland (Swaziland Railway, 2018). It is estimated that business opportunities to the value of R894 million ($65.7 million) in South Africa and R1.7 billion ($125 million) in Swaziland will be created (Asefovitz, 2017). Figure 3.14 shows a map of the links in rail network two, included in the case study.

3.2.2 GM2: Vehicle park restrictions

For the case study, two distinct vehicle parks were included for the model to choose from in each solution. GM2 is, thus, also a binary variable where $GM2 \in [1,2]$. The first vehicle park is a representation of the current vehicle park in use in the South African freight network. The second vehicle park is based on a growing number of countries planning on banning internal combustion engine (ICE) vehicles in the near future. In October 2016, Germany passed a resolution for a total ban on ICE by 2030 (Galeon, 2017). Norway plans to have 50% of new trucks be zero emissions vehicles.

India, France and the UK have already committed to banning petrol and diesel cars from 2030 or 2040 and the Netherlands and China are also considering such measures (Galeon, 2017). The second vehicle park will only consist of electric trucks and trains. There is no change to the vehicle park for air or water-based transport.

Tesla is launching a ground-breaking, heavy-duty, fully electric truck, the Tesla Semi, in 2019 (https://www.tesla.com/semi). Concurrently, Thor Trucks plan on converting fossil fuel burning trucks into battery-electric ones, with their prototype called the ET-One (Hawkins, 2017). A combination of the specifications of these truck prototypes have been used to model the electric trucks in the case study. Both prototypes are specified as US Class 8 vehicles, which has a gross vehicle weight rating exceeding 14 969 kg (Irfan, 2017) and both are limited to gross weights of 36 287 kg (Thompson, 2017; Thor Trucks, 2018). For the case study it was assumed that all four body shapes (tautliner, cattle carrier, tipper and tanker) can be fitted on these vehicles. There are, thus, a total of four truck types in this vehicle park. The commodity pairing will be the same per body shape as in the original vehicle park. Although Tesla has not supplied information on the tare mass of the Semi, Real Engineering estimates it will be around 7 711 kg (Thompson, 2017). With no data on the volumetric capacity for these vehicles available, as yet, it is assumed that their volumetric capacity will be similar to a regular 4 x 2 tractor trailers' (which are the closest in terms of specifications to these electric trucks).

It is proposed that (as is current practice in the world) the vehicle manufacturers will bear the cost of installing charge stations in the network (BusinessTech, 2017a), hence no capital expenses will be incurred for measure GM2. These "Megachargers" will be solar-powered (Etherington, 2017) and will, thus, not consume electricity from the existing power grid (Williams, 2017). An energy efficiency of 0.932 kWh/km is assumed in the case study, as estimated by Howard (2017) and a new energy source - solar electricity - will be added to the case study, for energy efficiency comparisons.

3.2.3 GM3: Taxes

The South African Government are proposing a carbon tax, which is to be implemented from 2018 onward (South African Ministry of Finance, 2017). It was decided to use this proposed tax to represent an economic freight transport energy management measure (GM3) in the case study. The measure is modelled as a binary variable, i.e. the tax is either levied in a solution, or not, where $GM3 \in [0,1]$.

Taxes are not regarded as an expense, but rather as a source of income for a government. The intention behind the imposition of a carbon tax speaks to the need to change behaviour, much more than the desire to generate inflows, however. Ideally, a tax will discourage unwanted behaviour to the extent that there is hardly any income generated from contravention of the tax specifications. The tax is modelled as a monetary penalty for unwanted behaviour, making it a soft constraint.

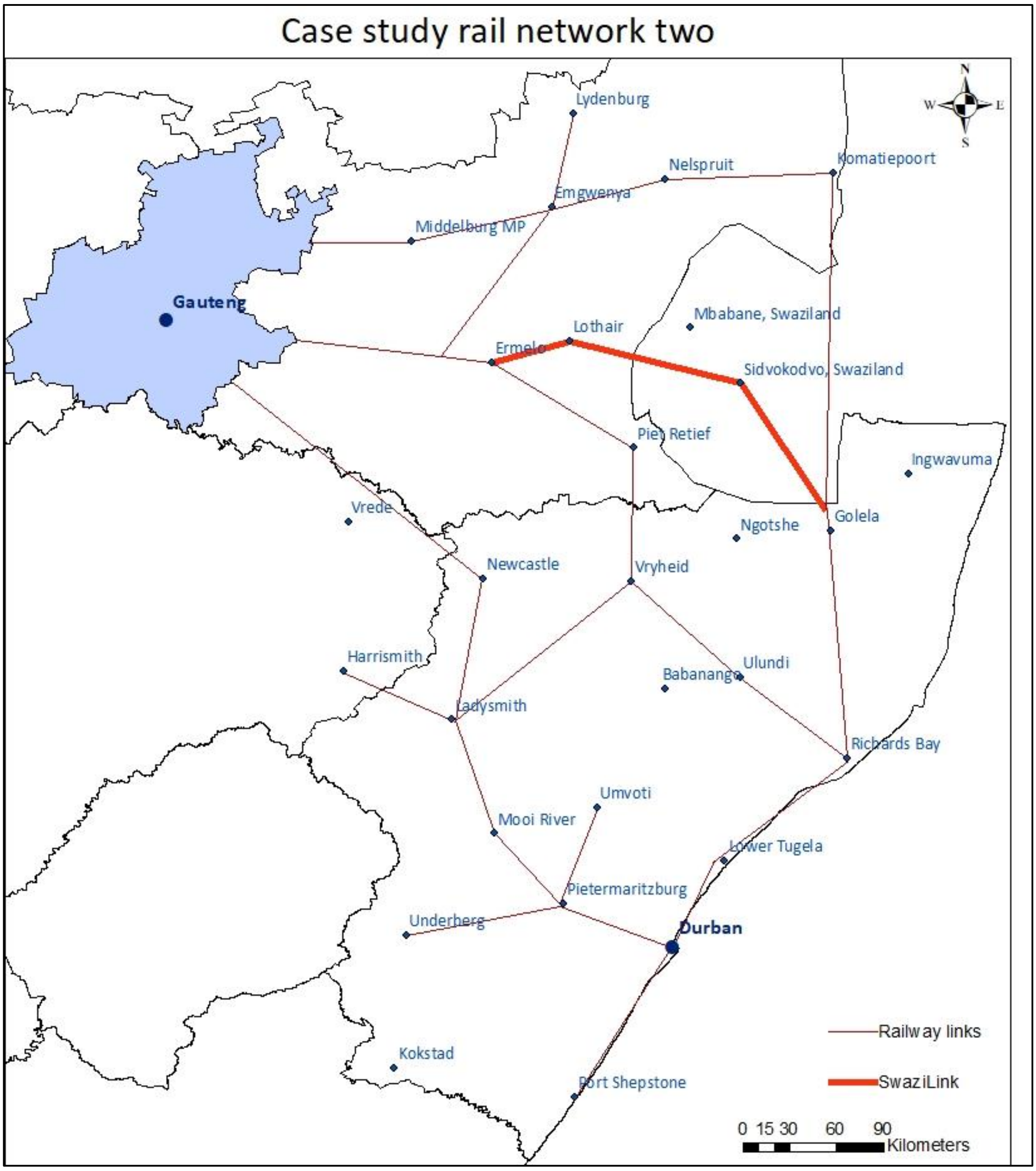


Figure 3.14 Rail network two included in the case study

3.2.4 GM4: Driver training

Improved driver practices (also called eco-driving) refers to a system of driving in which optimum fuel economy is achieved by the vehicle operator (Energy Exchange, 2018). This results from modifying a range of driving behaviours, such as smoother driving (gentle acceleration and braking), driving more slowly with less idling and looking ahead to anticipate traffic flow. The techniques employed can be tailored to a company's fleet and translated into a training curriculum. Studies show that beyond the significant fuel savings achieved, additional benefits can be accrued: drivers have been shown to experience lowered stress levels, increased confidence in vehicle handling and greater job satisfaction. An organisation can reduce its CO_2 emissions, reduce wear and tear on its fleet, develop a safer culture and effectively manage risk by reducing vehicle and personal injury (Energy Exchange, 2018).

While there is little doubt that the elements of improved driver practices can lower fuel consumption, questions remain about the permanence of the fuel savings after the initial intervention (Energy Exchange, 2018). Without regular practise of new skills and reinforcement by the employer, pilot programmes have shown that old behaviours may resurface. Ongoing training is, therefore, critical to long-term success. Pilot programmes have seen operators experience a reduction of up to 14% in fuel consumption (Energy Exchange, 2018). In 2007, the International Transport Forum concluded that once-off campaigns to encourage fuel-efficient driving tends to deliver fuel savings of 5%, compared with programmes that involve initial education, follow-up communication and ongoing monitoring and incentives, which delivered savings of up to 20% (Energy Exchange, 2018). Transport Scotland has a driver training programme, called FuelGood, that achieved a 14.8% improvement in fuel efficiency, on average, on the day of training over the past five years (Energy Saving Trust, 2018). SmartWay Transport (2009) claims that driver training programmes can improve fuel economy by 5%. Garfield Clean Energy (2018) corroborates these estimates, indicating driver training can achieve savings of 5% to 20%. Van der Voort, Dougherty and van Maarseveen (2001) developed a prototype fuel efficiency support tool which assists drivers in making behavioural adjustments and found that fuel consumption can be reduced by between 16% and 23% compared to normal driving behaviour.

Rail drivers can, in a similar fashion, also affect the fuel economy of rail operations. A simulation study by Hull *et al.* (2010) found that the adoption of an improved driving style in commuter rail can yield a 4% reduction in energy. TRAINER, a project aimed at improving energy efficiency by the railways in at least five EU-countries, found that training for freight operations need to be different than that of passenger operations, but both can be beneficial (TRAINER, 2010). The potential for energy savings in freight transport heavily depends on fluent transport on the track and the elimination of unexpected stops of the trains on the track and in front of entry signals (TRAINER, 2010). The findings of the TRAINER programme indicate that a 10% savings potential is a reachable and realistic goal - corroborating field tests from Deutsche Bahn in Germany showing that energy savings of 10% on average can be achieved, for both electric trains and diesel trains.

It is assumed that aircraft pilots and shipping captains, being highly skilled jobs, are already trained to operate the aircraft and vessels as efficiently as possible and that no further improvements will be achieved through additional training initiatives than those currently in use.

Decision variable GM4 represents the implementation of a training programme for freight operators. The variable is binary ($GM4 \in [0,1]$): if the training programme is not implemented the value of GM4 equals zero. If, however, the measure is implemented, a conservative average energy intensity improvement of 0.5% for road transport and 1% for rail transport is modelled. Implementation of such a programme would be a new expense. In the case study model a cost of R5 000 ($365) per driver is applied and it is assumed that one tenth of drivers can be trained in a year.

3.2.5 GM5: New technology

Developments in high-speed rail have, historically, been impeded by the difficulties in managing friction and air resistance, both of which become substantial when vehicles approach high speeds (De Chant, 2013). The "vactrain" concept theoretically eliminates these obstacles, by employing magnetically levitating (maglev) trains in evacuated (airless) or partly evacuated tubes, allowing for speeds of thousands of kilometres per hour. However, the high cost of maglev and the difficulty of maintaining a vacuum over large distances has prevented this type of system from ever being built (De Chant, 2013). Elon Musk and Richard Branson have joined forces to build such a transportation system, called Hyperloop One (https://hyperloop-one.com) and they aim to have three production systems in service by 2021.

This hyperloop is, essentially, a new proposed mode of transportation utilising the "vactrain" concept. It was decided to include this new transport mode - as a fifth mode - into the South African network model when the new technology measure (GM5) is applied. GM5 is also a binary measure, where $GM5 \in [0,1]$. This implies two additional network configurations to be used in the model, depending on the combined variable settings for GM1 and GM5. Network three is the same as network two, with the addition of a hyperloop on the most high-volume freight corridor in South Africa – the Durban to Gauteng route (Figure 3.6). A direct route connecting the Port of Durban with City Deep Container Terminal is assumed, spanning 497 km (Figure 3.15). At a cost of $17 million per mile, as estimated in the Hyperloop Alpha proposal (Taylor *et al.*, 2016), construction of this system would cost approximately $5.25 billion (which converts to near R71.4 billion at an exchange rate of R13.6/US $). Network configuration four is the original network configuration (i.e. without the SwaziLink), with the addition of the hyperloop.

When Taylor *et al.* (2016) considered the viability of hyperloop freight services, they found air freight to be the most likely market for hyperloop services, as it mainly entails transporting high value, time-sensitive cargo. This finding is corroborated in Machek *et al.* (2015). For this reason, all commodities that are paired with air cargo are paired with the hyperloop (including processed foods). The

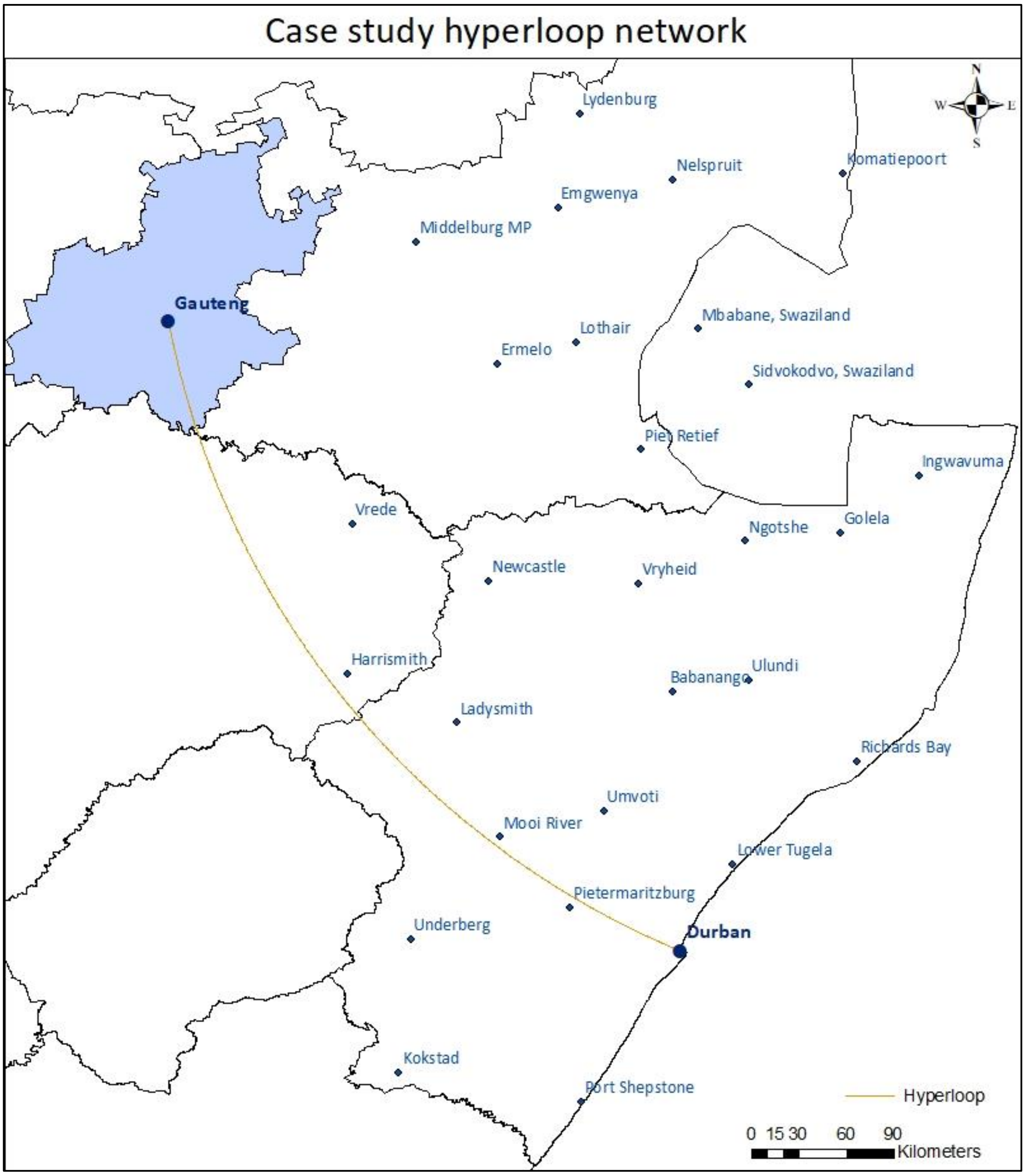


Figure 3.15 Hyperloop network included in the case study

Hyperloop One currently in development will be solar-powered (Vance, 2013) and can be completely self-sufficient in terms of energy supply (Ozgur, 2013). Ozgur (2013) estimated that power of 6 MW is needed for cruising, equating to 2 980 kWh to cover a 560 km track. Financing the solar panels required is part of the construction cost estimate, so no additional energy supply costs need to be incurred. Inclusion of the hyperloop does, however, add a sixth energy source to the model – solar electricity. Mack (2017) provides data on conceptual pod design dimensions. The cylindrical pods will be 30 m long, 2.7 m across and weigh around 20 tonnes, with an expected maximum payload of 40 tonnes (Wieringa, 2015).

3.2.6 GM6: Overload tolerance

A certain amount of overloading occurs on most road networks. The measure modelled here represents the amount of effort that is input to enforce the overloading regulations in the country with a view to limit the occurrence of overloading. The measure is applied in two ways. Firstly, the prevalence of overloading in the network is represented as the percentage of vehicles that are overloaded at various levels of enforcement of overloading regulation (summarised in Table 3.8). For example, if the level of enforcement is three out of five, then 10% of road vehicles are overloaded. Here, level one represents the highest level of enforcement and level five the lowest level of enforcement. The measure is applied by setting the decision variable $GM6_a$ to the level of enforcement (and, thus, the overloading prevalence) applicable for each mode for each simulation run. $GM6_{a,M} \in [1, \ldots, 5]\ \forall\ modes\ M$. It is assumed that in air freight, no overloading is allowed. This is because it is an operational priority to control the weight of air freight and overloading is typically avoided, due to the economic implications that would result from increased fuel consumption.

Table 3.8 Overloading prevalence parameters

Mode	Level of Enforcement				
	1	2	3	4	5
Road	1%	5%	10%	20%	30%
Rail	1%	2%	5%	7.5%	10%
Air	0%	0%	0%	0%	0%
Water	1%	5%	10%	20%	30%
Hyperloop	1%	2%	3%	4%	5%

When assessing the impact of overloading, it is not only how many vehicles are being overloaded that is important - by how much they are overloaded is just as important. The average overloading in the network on vehicles that are overloaded is represented as a tolerance for overshooting the maximum load that the vehicle is allowed to bear. The decision variable $GM6_b$ is modelled by assigning a level of average overload tolerance for each mode, in each vehicle assignment. $GM6_{b,M} \in [1, \ldots, 6]\ \forall\ modes\ M$. The corresponding tolerances per mode for this part of the measure is shown in Table 3.9. A tolerance of 0% implies that there is zero tolerance for overloading and all freight operators, thus, comply with the regulated load prescriptions. A tolerance of 25%, on the other hand, means that overloaded vehicles are overloaded by 25% of the maximum load prescriptions, on average. The hyperloop only has three tolerance levels for overloading: 1%, 5% and 10%, respectively, as the physics of transporting freight with the hyperloop does not allow a great degree of freedom in this regard.

Table 3.9 Overload tolerance measure parameters

Mode	Overloading Tolerance Level					
	1	2	3	4	5	6
Road	1%	5%	10%	15%	20%	25%
Rail	1%	5%	10%	15%	20%	25%
Air	0%	0%	0%	0%	0%	0%
Water	1%	5%	10%	15%	20%	25%
Hyperloop	1%	1%	5%	5%	10%	10%

3.2.7 LM1: Intermodal transport

Intermodal freight transport is the concept of combining two or more modes, to form an integrated transport chain aimed at achieving operationally efficient and cost-effective delivery of goods in an environmentally sustainable manner, from their point of origin to their final destination (Beytell, 2012). In this model, it is assumed that every freight operator has a choice whether or not to make use of intermodal shipping to transport a consignment of goods. This decision variable is modelled as a randomly generated binary variable, i.e. there is a 50% chance of shipping the goods as intermodal freight, or as unimodal freight ($LM1 \in [1,2]$). "Unimodal freight" implies that the same mode of transport is used along the entire route, from origin to destination. This choice is made once for all the demand of a certain commodity between an OD pair, but needs to be made anew for each OD pair.

3.2.8 LM2: Intramodal transport

Intramodal freight transport is characterised by competition for demand within a mode (Suarez, 2011), either by different companies competing to transport the freight in a similar manner, or by utilising different vehicles (mainly of different sizes) for different portions of a journey to capitalise on economies of scale. Logistics operators can decide whether or not they allow intramodal transfers along the route. This decision variable is modelled as a randomly generated binary choice, with a 50% chance of intramodal freight being allowed on the route, or not ($LM2 \in [1,2]$). For simplicity, it is assumed that the decision taken applies to all segments along the entire route between the OD pair in question.

3.2.9 LM3: Modal split

In this measure, the logistics choice of which modes to utilise for unimodal transport is captured. If demand between an OD pair is allowed to be met using intermodal transport (or if no unimodal transport routes exist), the modal split is implicitly generated based on the allocation of demand to various segments and various modes along the route. To model this decision variable, all the viable modes for unimodal transport between the OD pair and the total demand to be split needs to be known. A random sequence is developed to determine in which order the various modes will be assigned a randomly determined portion of the freight to be transported. The total assignment over all viable modes must equal the total demand needed to be split. Furthermore, every mode is only assigned a portion of the total demand once. LM3 is a continuous decision variable, where $0 \leq LM3_M \leq 1$, $LM3_M \in \mathbb{R}\ \forall\ modes\ M$ and $\sum_{m=1}^{M} LM3_m = 1$.

3.2.10 LM4: Route assignment

The logistics operator has a choice about the route to be taken between an OD pair. For unimodal freight, the demand assigned to each mode is split amongst the viable routes of that mode connecting the relevant OD pair by first generating a random sequence in which the routes will be assigned demand. A randomly determined portion of the demand is then assigned to each route in this random order. The sum of demand assigned to all viable routes must equal the demand assigned to the mode at hand. If there is only one viable route for a particular mode, all the demand is assigned to that route. The case study model considers a maximum of three different routes per OD pair and mode.

For intermodal freight, the model generates routes by combining segments with different modes of transport associated with each. Up to three intermodal routes are generated per OD pair and a random portion of the total demand is assigned to each of the routes in a random sequence, similar to the unimodal route allocation. LM4 is a continuous decision variable, where $0 \leq LM4_R \leq 1, LM4_R \in \mathbb{R}\ \forall\ routes\ R$ and $\sum_{r=1}^{R} LM4_r = 1$.

3.2.11 LM5: Vehicle assignment

There can be different vehicles to choose from for use within a mode. One dimension of choice is the size and load bearing capacity of the vehicle. The measure represented here aims to uncover the most apt vehicle assignment to be considered – a large fleet of smaller vehicles or a smaller fleet of larger capacity vehicles, for example. The continuous decision variable LM5 is modelled as a randomly assigned split in demand between the available vehicle types for the mode, route and commodity at hand. The demand is randomly split into the number of viable vehicle types and then assigned to the vehicle types in random order. $0 \leq LM5_V \leq 1, LM5_V \in \mathbb{R}\ \forall\ vehicles\ V$ and $\sum_{v=1}^{V} LM5_V = 1$.

3.2.12 LM6: Vehicle loading regimes

This measure addresses the average loading regime applied to vehicles in the network, i.e. it speaks to the volume of a vehicle's loading capacity that is utilised before the vehicle is deemed ready for a trip. In the case study model, vehicles are loaded normally distributed around a specified mean and standard deviation. To model this decision variable, the specified mean and standard deviation is modified. A higher mean translates to higher capacity utilisation and fewer trips required and a higher standard deviation represents lower conformity and more variance between transport operators. A commodity specific mean and standard deviation is used for each commodity and the alternative decision variable values considered for processed foods in the case study is listed in Table 3.10. For each commodity one of five means and one of two standard deviations can be selected per simulation. It is assumed that freight operators try to load vehicles close to capacity in order to be as efficient as possible, thus the means chosen for the case study range between the high end of the spectrum (from 75% to 95%). As the values of the mean alternatives differ in increments of 5%, the two alternatives for the standard deviation were chosen to be either slightly less than the mean step size (3%), or at the mean step size (5%). The same value for the mean and standard deviation is used in the entire simulation run, in order to be able to discern between better and worse loading regimes. LM6 is a two-dimensional discrete variable, where $LM6_a \in [1, \dots, 5]$ and $LM6_b \in [1,2]$.

Table 3.10 Vehicle loading regime measure parameters

Commodity	**Mean Alternatives**					**Standard Deviation Alternatives**	
Processed foods	75%	80%	85%	90%	95%	3%	5%

3.2.13 LM7: Propulsion system assignment

Vehicles of the same body type can often be equipped with different propulsion technology. This measure determines the preferred technology to be used in the network. In a similar fashion to the other assignment splits discussed, all viable propulsion systems are assigned a randomly divided portion of the total trips (in random order) and, hence, the total freight demand assigned to the vehicle, route, mode and commodity at hand. LM7 is a continuous decision variable, where $0 \leq LM7_P \leq 1, LM7_P \in\ \mathbb{R}\ \forall\ propulsion\ systems\ P$ and $\sum_{p=1}^{P} LM7_p = 1$.

3.2.14 LM8: Energy source assignment

A propulsion technology can sometimes accommodate various fuels, for example diesel trucks can operate on different quality diesel fuels (50 ppm or 500 ppm), or even biodiesel, without requiring modifications to the propulsion system. The measure modelled here acknowledges that the fuel used can influence various model performance metrics and represents fuel source selection as a logistics management measure. Again, all viable energy sources for use with a specific propulsion system are, in random order, assigned a random portion of the demand assigned to the propulsion system in question. LM8 is, thus, also a continuous decision variable, where $0 \leq LM8_E \leq 1, LM8_E \in \mathbb{R}\ \forall\ energy\ types\ E$ and $\sum_{e=1}^{E} LM8_e = 1$.

3.2.15 Summary of the mathematical formulation of the decision variables

Table 3.11 provides a summary of the decision variable definitions used in the case study model. Three variable types are dealt with: binary, discrete and continuous.

Table 3.11 Summary table of decision variable definitions used in the case study model

Decision Variables	**Decision Variable ID**	**Variable Type**	**Variable Expression**
Network design	GM1	Binary	$GM1 \in [1,2]$
Vehicle park restrictions	GM2	Binary	$GM2 \in [1,2]$
Taxes	GM3	Binary	$GM3 \in [0,1]$
Driver training	GM4	Binary	$GM4 \in [0,1]$
New technology	GM5	Binary	$GM5 \in [0,1]$
Overloading enforcement (a) and tolerance (b)	GM6	Discrete	$GM6_{a,M} \in [1, \dots, 5]\ \forall\ modes\ M$ $GM6_{b,M} \in [1, \dots, 6]\ \forall\ modes\ M$
Intermodal/unimodal routing	LM1	Binary	$LM1 \in [1,2]$
Intramodal split	LM2	Binary	$LM2 \in [1,2]$
Modal split	LM3	Continuous	$0 \leq LM3_M \leq 1, LM3_M \in \mathbb{R}\ \forall\ modes\ M$
Route split	LM4	Continuous	$0 \leq LM4_R \leq 1, LM4_R \in \mathbb{R}\ \forall\ routes\ R$
Vehicle split	LM5	Continuous	$0 \leq LM5_V \leq 1, LM5_V \in \mathbb{R}\ \forall\ vehicles\ V$
Vehicle loading regimes	LM6	Discrete	$LM6_a \in [1, \dots, 5]$ $LM6_b \in [1,2]$
Propulsion system split	LM7	Continuous	$0 \leq LM7_P \leq 1, LM7_P \in \mathbb{R}\ \forall\ propulsion\ systems\ P$
Energy source split	LM8	Continuous	$0 \leq LM8_E \leq 1, LM8_E \in \mathbb{R}\ \forall\ energy\ types\ E$

3.2.16 Summary of the case study decision variable alternatives

Table 3.12 provides a summary of the decision variable alternatives in the case study model.

Table 3.12 Summary of case study decision variable options

Decision variable	Decision variable ID	Case study decision alternatives
Network design	GM1	Existing transport network between Gauteng and Durban versus a network that includes the SwaziLink rail segments
Vehicle park restrictions	GM2	Existing mix of vehicles in use versus only solar-charged electric trucks available for road transport
Taxes	GM3	Included or excluded
Driver training	GM4	Included or excluded
New technology	GM5	Hyperloop connecting Gauteng to Durban included or excluded
Overloading tolerance and enforcement	GM6	One of five levels of enforcement and one of six levels of tolerance for each mode
Intermodal/unimodal routing	LM1	Included or excluded per OD pair
Intramodal split	LM2	Included or excluded per segment
Modal split	LM3	Road, rail, air, water and the hyperloop are alternative modes
Route split	LM4	The network specification dictates what routes can be formed
Vehicle split	LM5	5 Truck sizes and 4 body types, 7 locomotive types, 1 rail wagon type, 2 aircraft types and 1 type of ship
Vehicle loading regimes	LM6	One of five potential mean values and one of two standard deviation values
Propulsion system split	LM7	For road freight: ICE, hybrid-electric or full electric. For rail: diesel or electric locomotives. Jet engines for aviation and diesel engines for water-based freight
Energy source split	LM8	Diesel, biodiesel, electricity (coal-based), electricity (solar), jet fuel, bunker fuel

3.3 Defining the Assessment Criteria

The criteria that will be used to assess whether one selected set of values of the decision variables will be preferred over another needs to be defined as part of the problem formulation step. It is important that the stakeholders sign off on the methodology used to calculate or represent each criterion. Stakeholders need to specify the level of disaggregation required (for example: does an air pollution criterion need to be calculated as the sum of all the potential pollutant values or will a calculation of sulphur dioxide emissions alone suffice?). The stakeholders also need to specify the unit of measurement acceptable. In road safety, for instance, statistics can be expressed in terms of the number of injuries or the number of fatalities. There is a subtle distinction between these two specifications and, depending on the context and objective of the analysis, one might be more appropriate than the other, or both may need to be included. It is vital that stakeholders participate in the definition of the assessment criteria to be used and the specification of how it will be used.

Stewart (2015) suggests properties for a good set of assessment criteria as follows:

- *Value relevance*: Criteria need to be clearly linked to objectives, goals or values of the decision-maker(s).

- *Operational meaning and measurability*: Care is needed in defining criteria, so that the meaning of each is clearly and unambiguously understood by all participants. Then there must also be clarity as to how performance in terms of each criterion will be assessed, whether qualitative or quantitative.

- *Completeness, non-redundancy and conciseness*: There is conflict between ensuring that all important concerns have been captured but that, at the same time, the representation is sufficiently concise to allow informed judgement. In particular, care should be taken to avoid double counting. Given Miller's "magical number seven plus or minus two" (Miller, 1956), the decision analyst should, perhaps, aim at not more than nine criteria and certainly not more than fifteen to twenty at the outside.

- *Judgemental independence*: As far as possible, criteria should be defined such that values in terms of one criterion, or trade-offs between values for pairs of criteria, can meaningfully be assessed without needing to consider performance on other criteria. For some approaches, especially those based on weighted additive models, judgemental independence is critical to establishing the validity of results.

As mentioned in Section 1.2, freight transport impacts all three traditional pillars of sustainability: social, environment and economic. The impact of setting the value of a decision variable a certain way, thus, needs to be measured over multiple (in this case three) criteria. One approach to defining the assessment criteria used for this measurement is through the use of indicators. An indicator represents a distillation or abstraction of reality – a system element or variable chosen for its ability to describe a specific characteristic in the state of a system (Laedre *et al.*, 2015). "Indicators must be comprehensive in scope, must be multi-dimensional in nature (where appropriate) and must account for spatial differences" (Munasinghe, 2004).

A wealth of literature providing existing sets of sustainability assessment indicators (or describing the formulation of a set of sustainability assessment indicators) for various disciplines and applications exist and can provide guidance, or an initial point of departure, for defining the set of indicators to be used in a particular study. Decision-maker and stakeholder input is essential in terms of whittling the number of indicators down to an acceptable minimum that captures a satisfactory level of detail, but still remains manageable and practical. Bardos *et al.* (2009), EEA (2005), United Nations (2007) and OECD (2004) are a few good references to consult on the topic of sustainability indicators.

An example of a detailed analysis of the sustainability impacts of transportation and the relation between transport and climate change is provided in Lane-Visser *et al.* (2014). The focus in this study was mainly on environmental impacts of transport, but first, second and third order impacts were analysed and the indirect impacts on social criteria highlighted. The impacts were determined not only based on transport activity, but also the production and supply of energy to fuel the transport, as well as the provision of the necessary infrastructure and vehicles required to enable the transport activity.

Figure 3.16 shows the first order environmental impacts of transport. It was found that each component of the transportation system contributes towards many different first order impacts. Air pollution, water pollution and soil pollution appear to be the most severe impacts, as several different sources produce the same impact. From the diagram (Figure 3.16) it can be detected that transport activities generate the most impacts, followed by the supply of infrastructure, the supply of energy and, lastly, the supply of vehicles (in diminishing order). Please note that the impacts generated are not quantified; all impacts are regarded as equally significant in these diagrams.

Transport activity chiefly generates air pollution, contributes to the greenhouse effect and is solely responsible for noise pollution. The noise pollution during infrastructure construction is too short lived to be comparative. Infrastructure is, however, the key contributor to water and soil pollution (exacerbated by vehicle maintenance activities utilising the infrastructure). The main impacts, due to energy supply, are emissions, both in terms of air pollution and greenhouse gases. The second order impacts, which result from the impacts generated directly, are shown in Figure 3.17. The most dominant second order impact can be seen to be health impacts. Air, water and noise pollution contribute greatly to health impacts. Second to health impacts, are impacts on climate change and impacts on crops. Some first order impacts are repeated, but that is because that impact occurs as a consequence of other first order impacts, so the impact is both directly (first order) and indirectly (second order) effected. These impacts, both directly and indirectly attributable to transportation, are indicated with dashed lines (Figure 3.17). There are also third order impacts, resulting from the second order impacts (Figure 3.18). Some second order impacts result in the contribution to impacts that have already been generated by other sources (indicated by the dashed lines in Figure 3.18). These include: biodiversity, health impacts, water quality, climate change, agriculture and soil degradation (erosion). Many third order impacts also influence each other, but here the link to transportation as a source becomes tenuous and double counting becomes a possibility.

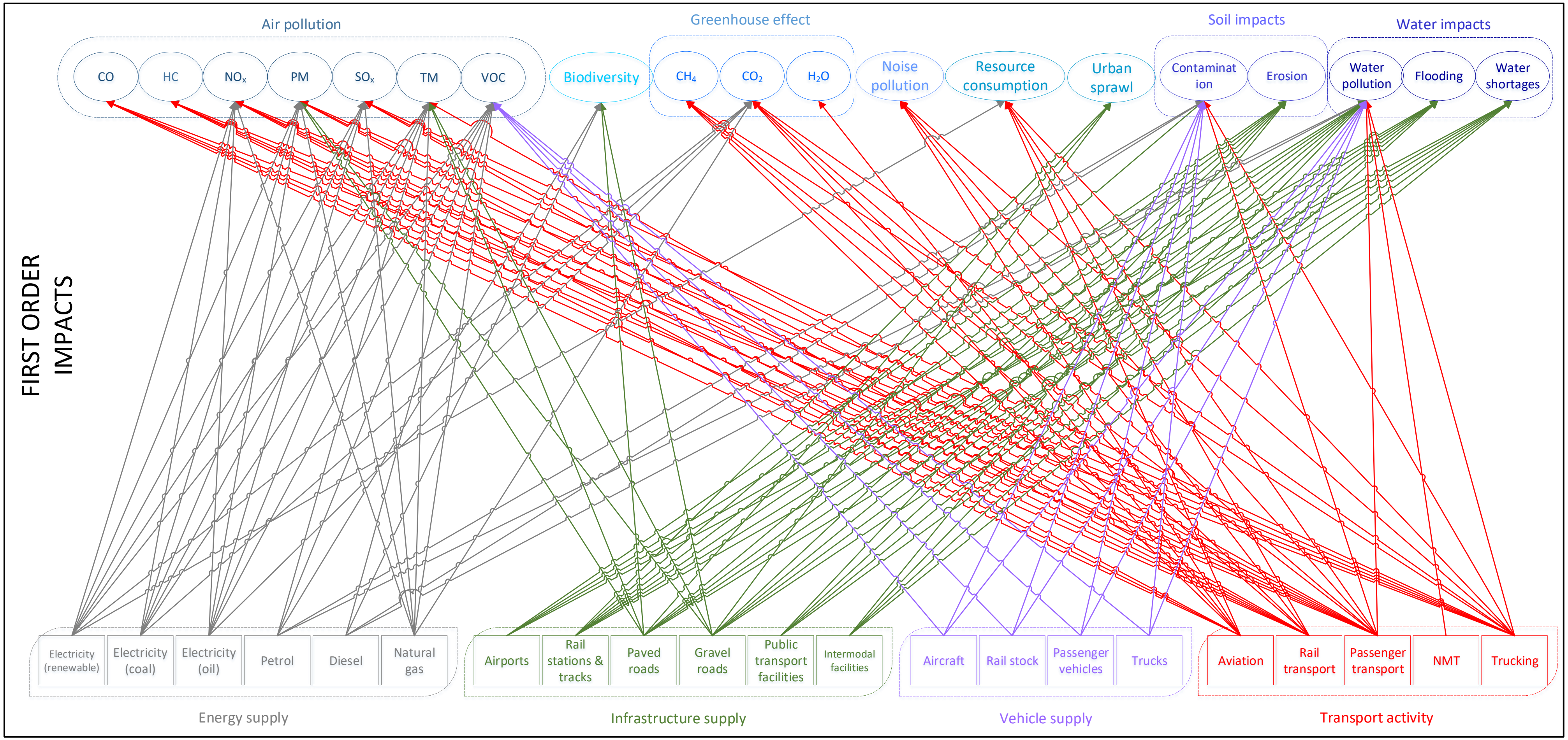


Figure 3.16 First order environmental impacts from transportation (Lane-Visser et al., 2014)

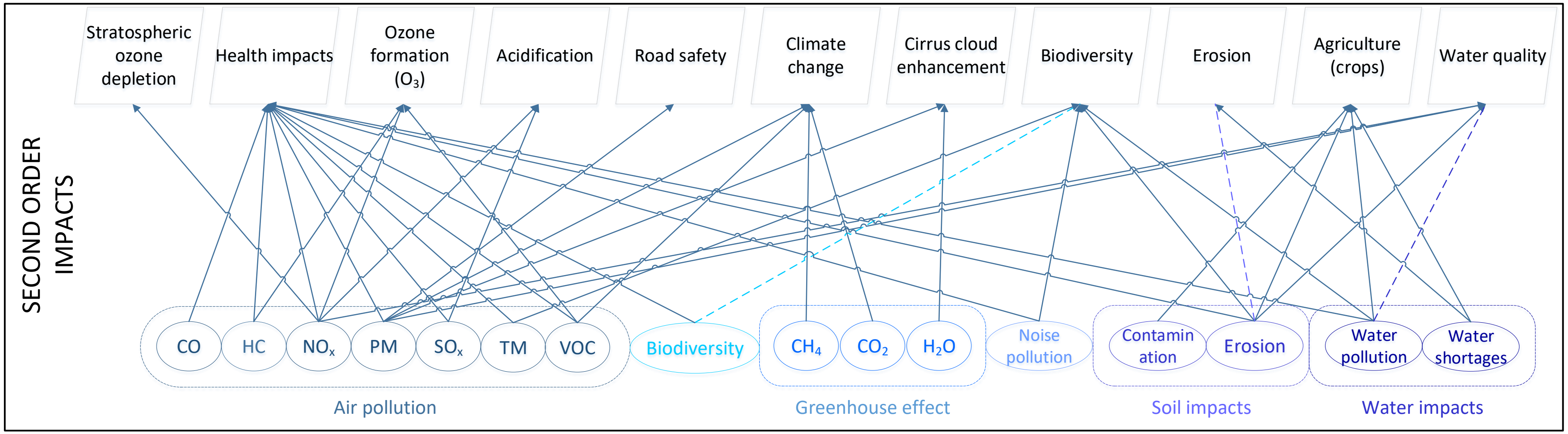


Figure 3.17 Second order impacts resulting from first order impacts (Lane-Visser et al., 2014)

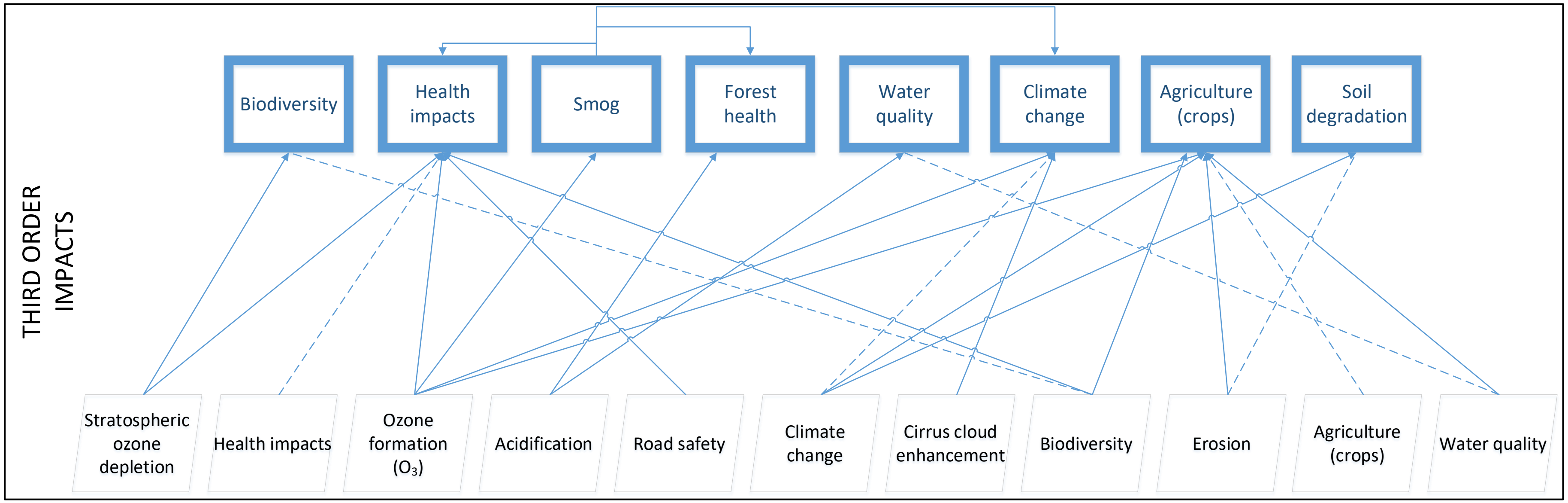


Figure 3.18 Third order impacts resulting from second order impacts (Lane-Visser et al., 2014)

The environmental indicators provided here illustrate the need for stakeholder participation - stakeholders will need to determine whether only first order, or whether first, second and third order impacts should be included in the analysis and they will need to specify whether all the indicators listed are of interest to them and the study at hand. Similar indicator sets, such as those published by United Nations (2007) and DEFRA (2013), can be used for the economic and social criteria, again requiring stakeholder input to determine the final set of indicators to be used. There needs to be a clear link between the indicators chosen and the decision variables used in the model.

Table 3.13 contains the set of sustainability criteria used for assessment of the performance of a set of decision variable settings in the case study. Once the assessment criteria are known and the decision variables have been defined, the relationship between the objective function and decision variables of the problem needs to be specified during the objective function formulation. The first question to answer, in terms of objective function specification, is whether the problem will be modelled as a single-objective or multiple objective problem. It is often possible to represent multiple criteria as constraints or weighted in a composite objective function, in order to restrict the model to a single objective formulation. A multi-objective optimisation model maximises or minimises more than one objective function at the same time (Rardin, 1998). "When goals cannot be reduced to a common scale of cost or benefit, trade-offs have to be addressed. Only a model with multiple objective functions is satisfactory, even though analysis will almost certainly become more challenging" (Rardin, 1998). Public sector applications commonly fall within this category of problems, as does the problem at hand. Each objective is assessed independently for each solution. The calculation of each of the objective function criteria is discussed in the remainder of Section 3.2.16.

Table 3.13 Sustainability indicators included in the case study assessment criteria

Economic Indicators	**Environmental Indicators**	**Social Indicators**
Capital expenditure	Total energy use	Jobs
Fuel costs	GHG emissions	
Taxes		
Maintenance		

3.3.1 Modelling the environmental objective

As the primary purpose of many freight energy mitigation measures is to reduce energy consumption in freight transport, the most logical criterion to represent the environmental objective is to calculate the total energy demand from freight transport in a specific network assignment. Better solutions will correspond to lower overall energy demand, implying that this is a minimisation problem. All energy sources, are, however, not equal in terms of the environmental and greenhouse gas pollution they cause and total GHG emissions are used as a criterion to determine whether the energy supply mix used is green, or not. The GHG emissions sub-objective is also a minimisation objective.

It was decided to combine both sub-objectives into a single composite objective function, without a weighting preference for one sub-objective over the other, rendering both sub-criteria equally important. To achieve this, the total score for each sub-objective needs to be indexed to the same scale, to enable adding them together without bias. Care needs to be taken that the order of magnitude of the scores for different solutions are adequately captured during this indexing exercise - a single unit increase should represent the relative change in values on the original scales appropriately. The final environmental objective function then becomes:

$$Environment = Energy + GHG\ emissions.$$

For calculation of the energy sub-criteria, the total energy demand per mode, expressed in megajoules (MJ), is calculated and summed together. Decision variable GM5 affects this calculation by specifying the number of modes considered in the model.

$$\begin{aligned} Energy\ (MJ) = {} & Road\ energy + Rail\ energy + Air\ energy + Water\ energy \\ & + (GM5 \times Hyperloop\ energy) \end{aligned}$$

For road transport the total energy demand per energy and truck type needs to be calculated per truckload, where possible. The total tonne-kilometres (tkm) driven by that type of truck, at that specific load, is multiplied by an energy intensity factor (expressed in MJ/tkm) relative to the load factor to determine total energy demand. The total energy value is summed together over all truckloads assigned in the network. The diesel energy intensity factors of the road vehicles used in the case study were documented by Eldestrand and Marin (2010) and are provided in Table 3.14. The table lists energy consumption values at payloads of 70% capacity and 100% capacity, respectively. Figure 3.19 illustrates the relationship between vehicle weight and fuel efficiency in trucks. All the polynomial regression lines indicate a near linear relationship between vehicle weight and fuel efficiency, regardless of travel speed. Exploiting this relationship, it was decided to use linear interpolation (based on the vehicle load) of the energy intensities provided in Table 3.14 to determine the specific fuel consumption of a loaded truck.

Table 3.14 Diesel truck energy intensity factors per vehicle type (reworked from Eldestrand and Marin, 2010)

Vehicle Description			Energy Intensity	
Vehicle Group	**Sample Vehicle**	**Vehicle Body**	**MJ/tkm @ 70%**	**MJ/tkm @ 100%**
Rigid Trucks	Isuzu FTR 850	Tautliner	1.82	1.34
		Tipper	2.43	1.78
		Tanker	1.86	1.36
4x2 truck tractor and 2 axle semi-trailer	Mercedes-Benz ACTROS 2036S/36	Tautliner	0.99	0.76
		Tipper	1.29	0.86
		Tanker	1.02	0.78
6x4 truck tractor and 2 axle semi-trailer	Powerstar 2642S VX 6x4	Tautliner	0.85	0.69
		Tipper	1.04	0.82
		Tanker	0.87	0.70
6x4 truck tractor and 3 axle semi-trailer	Renault C440.26 6x4 TK E6	Tautliner	0.76	0.61
		Tipper	0.93	0.73
		Tanker	0.78	0.63
Interlink or drawbar	MAN TGA 26.480 6x4 BLS	Tautliner	0.72	0.58
		Tipper	0.86	0.76
		Tanker	0.75	0.54

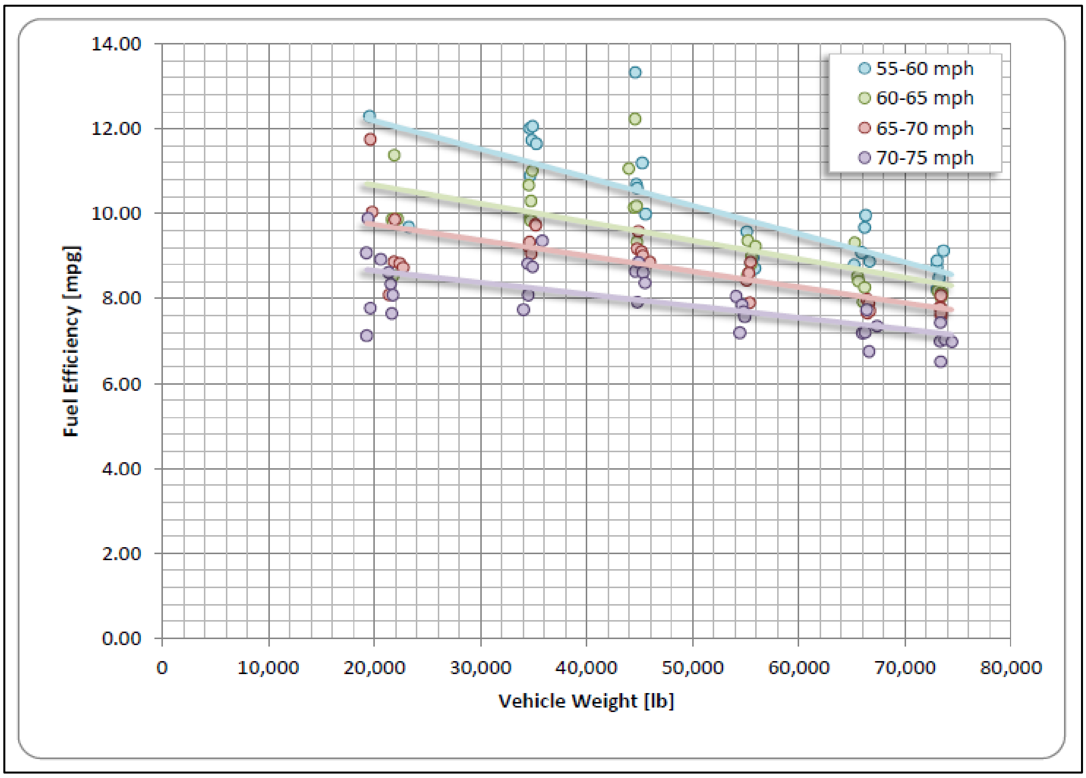


Figure 3.19 Fuel efficiency versus vehicle weight at different speed intervals on flat terrain (Franzese, 2011)

Diesel energy demand in the network is, thus, calculated by:

$$Diesel\ (MJ) = \sum_{v=1}^{V} \sum_{l=1}^{L} tkm_{v,l} \times energy\ intensity_{v,l}$$

where

V = the total number of diesel truck types included in the model, $V \in [1, \dots, 5]$,

L = the total number of load configurations assigned in the model. This is unknown at this stage, as it depends on the values of decision variables GM6, LM1, LM2, LM3, LM4, LM5, LM6, LM7 and LM8 for every assignment decision in the network.

$tkm_{v,l}$ = The total tkm assigned to diesel vehicle type *v* at load *l* in the network, and

$energy\ intensity_{v,l}$ = the energy intensity of diesel vehicle type *v* at load *l* expressed in MJ/tkm.

It is noteworthy that as vehicle weight increases, the energy intensity rate decreases. This somewhat counter-intuitive feature exists due to the incremental fuel consumption increase for higher loads being less than the accompanying increase in tonnes transported and the efficiency per tkm, thus, improves. On a side note - it would make interesting future research to expand on the level of detail included in this assessment, where the gradient, average speed and condition of the road and its impacts on fuel efficiency, as documented in Franseze (2011), are also considered. With the case study serving only as a demonstration vehicle, this was deemed beyond the scope of the analysis at hand.

For trucks utilising biodiesel, in turn, no load-related distinction is made in terms of their energy intensities, due to a lack of reliable data. The energy intensities can range between 0.5917 MJ/tkm for canola-based biodiesel and 0.5022 MJ/tkm for biodiesel from photo-bioreactors (Borowitzka and Moheimani, 2013). The more conservative canola-based biodiesel is assumed for use in the case study.

The formula to calculate biodiesel demand is:

$$Biodiesel\ (MJ) = tkm \times 0.5917$$

where

tkm = the total tkm assigned to biodiesel trucks in the network.

In a report to the European Commission DG Climate Action, the Ricardo-AEA consultancy firm (2011) estimated that hybrid heavy delivery vehicles can achieve a 7% improvement on conventional diesel engines over long-haul trips. The steps to calculate total fuel consumption from hybrid trucks is, thus, to first calculate what the regular diesel energy demand would be if those hybrid trips were performed by regular diesel trucks, after which the total is reduced by 7%.

$$Hybrid\ (MJ) = Diesel\ \times 93\%$$

It is important to ensure that the tkm values used for these calculations include all tkm from both loaded trips, as well as any empty return trips that the trucks need to make. Decision variable GM2 also plays a part in determining road energy demand in the network, by setting the type of trucks available for use in the network.

$$Road\ energy\ (MJ) = \begin{cases} Diesel + Biodiesel + Hybrid & ,GM2 = 1 \\ Electric & ,GM2 = 2 \end{cases}$$

When electric trucks are used, the energy calculation for road transport becomes:

$$Electric(MJ) = \sum_{l=1}^{L} 3.3552 \times \frac{tkm_l}{vehicle\ weight_l}$$

where

tkm_l = the total tkm assigned to electric trucks carrying load *l* in the network, $L \in [1, \dots, x]$,

$vehicle\ weight_l$ = the vehicle weight of a truck carrying load *l*, $L \in [1, \dots, x]$.

The energy intensity factor for electric trucks is expressed in MJ/km, hence the tonnages need to be removed from the equation by dividing the tkm with the applicable vehicle weight. The number of vehicle load categories assigned is dependent on decision variables GM1, GM5, GM6, LM1, LM2, LM3, LM4 and LM5 and is denoted with the symbol *x* to represent this uncertainty.

Finally, decision variable GM4 affects the overall energy efficiency depending on whether driver training occurs or not. If driver training is provided, total energy demand from road freight is improved by 0.5%.

$$Road\ energy\ (MJ) = \begin{cases} Road\ energy & ,GM4 = 0 \\ Road\ energy\ \times 0.995 & ,GM4 = 1 \end{cases}$$

To calculate the energy demand from rail transport assigned in the network, the total tkm per track type is multiplied with the energy intensity factor for that track type. Transnet data on the average energy intensity factors (expressed in MJ/tkm or Wh/tkm, respectively) for the diesel (Feris, 2010) and electrified (Transnet Freight Rail, 2007) rail networks were used (Table 3.15). These values are based on gross tonne-kilometres, i.e. it accounts for the complete train configuration of wagons and locomotives. Watt-hours (Wh) are converted to megajoules (MJ) by the relation 1 kWh = 3.6 MJ. Again, the tkm values used include both empty and loaded trips' tkm.

Table 3.15 Energy intensity of rail freight

Rail Track Type	Energy Intensity	
	MJ/tkm	Wh/tkm
Diesel (non-electrified)	0.436	
3 kV DC		23.03
25 kV AC		16.9

The following formula is used to calculate rail energy demand:

$$Rail\ energy\ (MJ) = (tkm_{diesel} \times 0.436) + (tkm_{3kV} \times 0.082908) + (tkm_{25kV} \times 0.06084)$$

GM4, however, impacts the energy efficiency of rail transport. If driver training is provided, the overall energy use by rail freight is reduced by 1%. The formula for the calculation of rail energy must, thus, be adapted to:

$$Rail\ energy\ (MJ) = \begin{cases} Rail\ energy & ,GM4 = 0 \\ Rail\ energy\ \times 0.99 & ,GM4 = 1 \end{cases}$$

Energy intensity factors for air freight (expressed in MJ/tkm) and water-based freight (expressed in J/tkm) were obtained from van Essen *et al.* (2003) and are displayed in Table 3.16. Air freight energy intensities vary depending on the distance travelled, as shown in the table.

Table 3.16 Energy intensity of air and water freight

Vehicle	Energy Intensity	
	MJ/tkm	J/tkm
Air freight 500km range	11.9	
Air freight 1500km range	9	
Cargo ship		0.19
Tanker		0.36

The formula to calculate air freight energy demand is:

$$Air\ energy\ (MJ) = (tkm_{\leq 500km} \times 11.9) + (tkm_{>500km} \times 9)$$

where

$tkm_{\leq 500km}$ = the total tkm (empty and loaded combined) for air freight trips covering a distance shorter than or equal to 500 km, and

$tkm_{>500km}$ = the total tkm (empty and loaded combined) for air freight trips covering a distance further than 500 km.

In a similar fashion, the water freight energy demand is calculated by:

$$Water\ energy\ (MJ) = \sum_{v=1}^{V} tkm_v \times \frac{energy\ intensity_v}{1\ 000\ 000}$$

where

tkm_v = the total tkm (empty and loaded) assigned per vessel *v* in the network, $V \in [1,2]$, and

energy intensity$_v$ = the energy intensity factor per vessel *v*, $V \in [1,2]$, expressed in J/tkm.

The hyperloop's energy demand is calculated by multiplying the total tkm assigned to the hyperloop (full and empty trips combined) with the appropriate energy intensity factor (19.17 MJ/km). Because this energy intensity is also specified in terms of km, and not tkm, the vehicle weight needs to be part of the equation similar to that for electric trucks.

$$Hyperloop(MJ) = \sum_{l=1}^{L} 19.17 \times \frac{tkm_l}{vehicle\ weight_l}$$

where

tkm_l = the total tkm assigned to the hyperloop at load *l* in the network, $L \in [1, \ldots, x]$, and

vehicle weight$_l$ = the vehicle weight of the hyperloop pods at load *l*, $L \in [1, \ldots, x]$.

Greenhouse gases are gaseous constituents of the atmosphere, both natural and anthropogenic, that absorb and re-emit infrared radiation and includes carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs) and sulphur hexafluoride (SF_6) (South African Ministry of Finance, 2017). South Africa's draft carbon tax bill (South African Ministry of Finance, 2017) lists the GHG emissions factors of various transport fuel types in carbon dioxide equivalent (CO_2e) values per tonne (Table 3.17). "Carbon dioxide equivalent means the concentration of carbon dioxide that would cause the same amount of radiative forcing (the difference of sunlight absorbed by the earth and energy radiated back to space) as a given mixture of carbon dioxide and other greenhouse gases" (South African Ministry of Finance, 2017). These values are used to determine GHG emissions in the case study model. Before these factors can be utilised, however, a consumption value per fuel type needs to be determined. This is done by converting the total energy demand per fuel type (in MJ) to a tonne value by dividing the energy used by the energy density of each fuel type (in MJ/t), as provided in Table 3.18. These calculated tonnages are then multiplied by the GHG emissions factors listed in Table 3.17 and summed together to estimate the total GHG emissions (in CO_2e) of the transport assignment in the relevant iteration of the case study. It is assumed that solar electricity emits no GHG emissions. Biodiesel from canola oil reduces GHG emissions by 92.5% compared to petroleum diesel fuel used in large heavy-duty trucks ((S&T)[2] Consultants Inc, 2010).

The formula to calculate the total GHG emissions is:

$$
\begin{aligned}
GHG\ emissions\ (CO_2e) \\
&= \left(\frac{Diesel\ MJ_{road}}{42\ 773} \times 2.8706\right) + \left(\frac{Diesel\ MJ_{rail}}{42\ 773} \times 3.1494\right) \\
&+ \left(\frac{Biodiesel\ MJ}{37\ 800} \times (2.8706 \times 0.075)\right) + \left(\frac{Jet\ fuel\ MJ}{46\ 400} \times 2.4732\right) \\
&+ \left(\frac{Residual\ fuel\ oil\ MJ}{44\ 000} \times 3.2512\right) + \left(\frac{Electricity_{rail}\ MJ}{19\ 680} \times 1.8545\right)
\end{aligned}
$$

Table 3.17 GHG emissions factors for transport fuels (South African Ministry of Finance, 2017)

FUEL TYPE	GHG EMISSION FACTOR (CO_2e) PER TONNE
AVIATION GASOLINE	2.3977
COMPRESSED NATURAL GAS	N/A
DIESEL	2.8706
DIESEL –OFFROAD	3.1497
DIESEL-RAIL	3.1494
JET KEROSENE	2.4732
KEROSENE	2.6694
LIQUEFIED NATURAL GASES	N/A
LIQUEFIED PETROLEUM GASES	1.7244
LUBRICANTS	2.9566
NATURAL GAS	2.4233
OTHER KEROSENE	2.6694
OTHER PETROLEUM PRODUCTS	2.9566
PARAFFIN WAXES	2.9566
PETROL-LOW MILEAGE LDV	2.4305
PETROL-OXIDATION CATALYST	2.4707
PETROL-UNCONTROLLED	2.4284
REFINERY GAS	2.8538
RESIDUAL FUEL OIL – WATER	3.2512
SUB-BITUMINOUS COAL – RAIL	1.8545

Table 3.18 Energy densities of various fuel types. Compiled from (Hofstrand, 2008; DNV GL, n.d.; ESKOM, 2015; Theoretical Astrophysics Center at UC Berkeley, n.d.)

Fuel Type	MJ/t
Diesel	42 773
Biodiesel	37 800
Jet kerosene	46 400
Residual fuel oil	44 000
Electricity (coal)	19 680

3.3.2 Modelling the economic objective

The economic impacts included in the case study represent the monetary impact of the freight transportation assignment and of the measures invoked. Seeing that the sub-components of this objective are expressed as cost functions, a desirable solution will yield a lower cost. This objective, thus, also needs to be minimised. Expenditures can be split into capital expenses (such as building new infrastructure) and operating expenses (such as the cost of fuel and taxes). Capital expenses are lump sums that need to be spent once per project, whereas operating expenses are incurred per unit of transport activity and are directly proportional to the volume of transport activity. Maintenance is an additional sub-criterion that will be addressed somewhat differently. It is acceptable to add the values of the sub-criteria that can be expressed in a monetary form (South African Rand) together to determine the total cost of a network assignment. The maintenance economic impact is, however, not expressed in terms of Rands, but rather in terms of the total maintenance requirements of a particular network assignment, which correlates directly to the required spend on maintenance. The sum of the three monetised sub-criteria and the value for the maintenance impacts each have to be normalised before they can be added together to form the economic objective value. The formula to calculate the economic objective is:

$$Economic = \left(Capital + Fuel + (Taxes \times GM3)\right) + Maintenance$$

Decision variable GM3 determines whether or not taxes are included in a solution. It should be noted that, although certain elements of the economic objective value are expressed in terms of Rands, the absolute value of this objective has no real meaning. It is the relative value of this objective as it varies between solutions that convey the information for decision-makers, allowing for ranking and comparison between the different solutions. Please also note that the indirect costs associated with the implementation and management of the freight energy management measures are not included in the objective function value estimation. The intention of this model (as specified in this document) is not to determine a specific budget allocation, nor a return on investment analysis. The objective is to prioritise policies and the model proposed here will provide information on which policies to pursue and which to disregard. With this short list of preferred policies, a more tactical budget allocation analysis can be performed. It is, however, possible to expand the model to account for this, should the stakeholders and the problem require it.

Measures GM1, GM4 and GM5 can affect capital expenses, as these measures necessitate a change in infrastructure or represent the introduction of something new that will incur fees not previously incurred in the network. If these measures are applied in an assignment, the costs associated with them are added to the total capital cost function:

$$Capital\ (R) = \begin{cases} SwaziLink\ cost + (GM4 \times Training\ cost) + (GM5 \times Hyperloop\ cost), & GM1 = 2 \\ (GM4 \times Training\ cost) + (GM5 \times Hyperloop\ cost) & , GM1 = 1 \end{cases}$$

where

$$Training\ cost = (Jobs_{road} + Jobs_{rail}) \times 0.1 \times R5\ 000$$

The operational expenses included are fuel costs and taxes. Labour costs (another typical operational expense) are not included here, because, although labour costs are an expense for the freight operators, the economic impact of wages being paid is beneficial, both in an economic and social sense. Reflecting it as a cost to be minimised would be misleading.

Fuel costs are also operational expenses paid by the freight carriers, but because South Africa is a net oil importer, a lot of this money indirectly leaves the country, which is less beneficial to the local economy. Additionally, if the cost of fuel forces the cost of freight transportation to go up, it can lead to an increase in inflation as the cost of goods increase for the end consumer. Fuel is the biggest contributor to road transport costs (Havenga *et al.*, 2015); it is beneficial to keep the expenditure on fuel as low as possible, so this is included as part of the economic objective function specification.

Fuel costs are calculated on the total quantity of fuel used in the traffic assignment. The retail price of biodiesel was R11.86/l on 15/11/2017 (Craig, 2017). The comparative price of wholesale 0.05% diesel in November 2017 was R12.36/l (BusinessTech, 2017b). For ease of use (and because the total tonnage consumed per energy source also needed to be estimated for the environmental assessment) all fuel costs are converted to a R/t value using a density of 0.8368g/cm^3 for diesel and an average of 0.88225g/cm^3 for biodiesel (Alptekin and Canakci, 2008). The costs used in the case study are shown in Table 3.19. An exchange rate of R13.6/US$ (the spot rate at 12:30pm on 12 December 2017) is used in all currency conversions. The Durban IFO180 bunker fuel price on 11/12/2017 of $381.5/metric tonne was obtained from Ship and Bunker (2017). IATA (2017) published the price of aviation jet fuel as at 1 December 2017 for Africa and the Middle East at $583.8/metric tonne.

Table 3.19 Fuel prices used in case study

Fuel Type	R/t	R/l
Diesel	14770.55	12.36
Biodiesel	13442.9	11.86
Jet kerosene	7939.68	6.528
Residual fuel oil	5188.4	5.19

The electricity tariff for electrified rail is based on the average value of R531.49/MWh paid by Transnet Freight Rail in 2016 (this was deduced based on information provided in their annual financial statements (Transnet, 2017) and their sustainability report (Transnet, 2016b)). This equates to R147.64/GJ. The hyperloop will be a fully self-contained solar system (Ozgur, 2013), thus, no external fuel costs are applicable. It is assumed that the same price for rail electricity will be charged for recharging an electric truck. Fuel costs are calculated as:

$$\begin{aligned} Fuel\ (R) = {} & (Diesel_{road} + Diesel_{rail}) \times 14\,771 + Biodiesel \times 13\,443 + Jet\ kerosene \times 7\,940 \\ & + Residual\ fuel\ oil \times 5\,188 + (Electricity_{rail} + Electricity_{road}) \times 147.64 \end{aligned}$$

Total fuel costs are affected by the values set for all the decision variables, except GM3 (taxes). The tax variable is actually a monetary penalty for unwanted behaviour, implemented as a soft constraint included in the economic objective function as a cost to be minimised. The draft carbon tax bill (South African Ministry of Finance, 2017) proposed by the South African Government identifies three tax bases – fossil fuel combustion, fugitive emissions and industrial process and product use. In this case study, freight transport impacts are assessed based only on the impacts generated during the actual transportation event and, thus, the fugitive emissions generated in the supply of the energy sources (namely oil and coal), as well as emissions from industrial processes and product use, are excluded from the calculations. Direct fossil fuel combustion occurs in road and rail freight utilising regular diesel, as well as in aviation and maritime transport. The hyperloop uses clean energy and will be exempt from a carbon tax.

The carbon tax bill explains the calculation of the emissions as follows: *"The carbon tax must be levied in respect of the sum of the greenhouse gas emissions of a taxpayer in respect of a tax period expressed as the carbon dioxide equivalent of those greenhouse gas emissions resulting from fossil fuels combustion in respect of that tax period that is a number constituted by the sum of the respective numbers determined for each type of fossil fuel in respect of which a greenhouse gas is emitted in respect of that tax period which respective numbers must be determined in accordance with the formula: E = (A x B) in which formula "E" represents the number to be determined, "A" represents the mass of any one type of the fossil fuel expressed in tonne that is the source of the greenhouse gas emission, other than any fuel utilised for the purposes of international aviation and maritime transport, and "B" represents the greenhouse gas emission factor in carbon dioxide equivalent per tonne that must be determined by matching the type of fossil fuel of which the mass is determined in terms of* [Table 3.17]*"* (South African Ministry of Finance, 2017).

The rate of the carbon tax is set at R120 ($8.8) per tonne carbon dioxide equivalent of the total greenhouse gas emissions of a taxpayer in the tax period. The tax period, in turn, is set as the period commencing on 1 January of each year and ending on 31 December of that year. As the carbon tax is calculated as a lump sum based on overall emissions during a year, this corresponds with the data in the case study representing the total freight demand in a year. The formulae from the carbon tax bill can, thus, be readily applied in the case study model. The bill calculates the amount of tax payable in respect of the total fossil fuel combustion related greenhouse gas emissions with the formula:

$$X = \{(E - D - S) \times (1 - C) \times R\}$$

where

> *X* = the total tax payable amount to be determined (in Rands),
>
> *E* = the number in respect of the total fossil fuel combustion related greenhouse gas emissions of the taxpayer in respect of that tax period, expressed as a carbon dioxide equivalent determined in terms of the formula for the calculation of *E* described in the quote,
>
> *D* = the number in respect of the petrol and diesel related greenhouse gas emissions of that taxpayer in respect of that tax period, expressed as a carbon dioxide equivalent determined in terms of the formula for the calculation of *E* described in the quote,
>
> *S* = the number in respect of greenhouse gas emissions, expressed in terms of carbon dioxide equivalent, that were sequestrated in respect of that tax period as verified and certified by the Department of Environmental Affairs. For the purposes of this section, "sequestrate" means the process of increasing the carbon content of a carbon reservoir other than the atmosphere,
>
> *C* = the sum of percentages of allowances as determined in the draft bill in respect of that tax period, and
>
> *R* = the rate of tax prescribed at R120/tonne.

Where the number in respect of the determination of the expression (*E* – *D* – *S*) in the formula is less than zero, that number must be deemed to be zero. In this formula, all diesel related emissions are excluded from the taxable emissions. It is assumed that this will also be the case for the use of biodiesel in road transport. Furthermore, maritime transport is also excluded from the tax base. This yields only emissions generated by domestic aviation to be taxed in the case study. The emissions related to electrified rail will be taxed under the supply of energy sources and not under mobile emissions, hence this also falls outside the scope of these calculations. At present, no carbon sequestration activities are undertaken by the aviation sector in South Africa and the value of S is assumed to be zero.

There are certain tax allowances specified in the draft bill. A taxpayer that conducts an activity that is listed in Table 3.20 in the column "Sector" may receive an allowance of 60% of the total percentage of greenhouse gas emissions in respect of a tax period in respect of that activity. Civil aviation qualifies for a basic tax-free allowance on 60% of fossil fuel combustion emissions. Further to this, a trade exposure allowance in respect of the export of goods out of the country is available. No cross-border air transport is included in the case study network; hence this allowance is excluded from further analysis.

The calculation of the carbon tax value used in the case study's economic objective function is, thus, reduced to: $Taxes\ (R) = (A \times 2.4732) \times 0.4 \times 120$ where A equals the total tonnes of jet kerosene consumed in the network. The tax sub-criterion is only affected by decision variables that affect the volume of air freight in the network, or GM3 that determines whether the tax is levied or not. This includes variables GM1, GM3, LM1, LM2, LM3, LM4, LM5 and LM6. There is no tolerance for overloading in aviation and all aviation vehicles utilise the same propulsion and energy sources, so decisions on these variables will not affect overall jet kerosene consumption volumes.

Maintenance of transport infrastructure is a large government cost, which needs to be minimised. Equivalent single axle loads (ESALs) are typically used as a measure of pavement damage caused by the passage of a loaded axle, relative to that caused by an axle of a standard weight (Transportation Research Board, 1996). In South Africa, ESALs are referred to as E80s, where an E80 is an equivalent 80 kN axle load (SANRAL, 2014). Because the cost of transport surface infrastructure maintenance will be proportional to the amount of ESALs in the network, it was decided that a calculation of the ESALs per mode would sufficiently represent the economic impact of a network assignment on infrastructure maintenance.

Roads in South Africa are designed in one of four categories: major inter-urban freeways and major rural roads (Category A), inter-urban collectors and rural roads (Category B), lightly trafficked rural and strategic roads (Category C) and rural access roads (Category D) (SANRAL, 2014). Each road category is designed for a different total equivalent traffic loading before resurfacing or structural rehabilitation will be required, expressed in terms of E80s/lane. The values associated with each category are provided in Table 3.21. The greater the amount of E80s on a paved segment, the shorter the lifespan of that paved segment will be. It is, thus, desirable to keep ESALs as low as possible. This can be achieved by spreading loads evenly throughout the network and not concentrating loads on certain network segments only. Alternatively, because pavement damage increases exponentially as the weight of an axle increases, more vehicles that are smaller, with lower axle loads, could also be used.

Table 3.20 Tax allowances specified in Schedule 2 of the Draft Carbon Tax Bill *(South African Ministry of Finance, 2017)*

Sector	Basic tax-free allowance for fossil fuel combustion emissions %	Basic tax-free allowance for process emissions %	Fugitive emissions allowance %	Trade exposure allowance %	Z-factor allowance %	Carbon budget allowance %	Offsets allowance %	Maximum total allowances %
specified industry								
Transport								
Civil aviation	60	0	0	10	5	5	10	90
Road transport	60	0	0	10	5	5	10	90
Railways	60	0	0	10	5	5	10	90
Water-borne navigation	60	0	0	10	5	5	10	90
Other transport	60	0	0	10	5	5	10	90
Other Sectors								
Commercial; institutional	60	0	0	10	5	5	10	90
Residential	100	0	0	0	0	0	0	100
Agriculture; forestry; fishing/Fish farms	60	0	0	10	5	5	10	90
Non-specified								
Stationary	60	0	0	10	5	5	10	90
Mobile	60	0	0	10	5	5	10	90
Multilateral operations	60	0	0	10	5	5	10	90

The formula to calculate the ESALs in road freight is (CSIR Transportek, 2005):

$$ESAL = \left(\frac{P}{P_s}\right)^4$$

where

P = the axle load for which the ESAL needs to be determined, and

P_s = standard axle load, taken as 8 200 kg.

This formula needs to be applied to each axle in a truck - the sum of all axles will represent the total ESALs generated by the vehicle. There are different equivalency factors applicable for tandem and tridem axles, to properly scale the calculations. The factors provided by (Transportation Research Board, 1998) were used in this model.

Table 3.21 Definition of road categories in South Africa (SANRAL, 2014)

	Road Category			
	A	**B**	**C**	**D**
Description	Major inter-urban freeways and major rural roads	Inter-urban collectors and rural roads	Lightly trafficked rural roads, strategic roads	Rural access roads
Importance	Very important	Important	Less important	Less important
Level of service	Very high	High	Moderate	Moderate
Typical Pavement Characteristics				
Approximate design reliability (%)	95	90	80	50[1]
Length of road exceeding terminal distress condition at end of structural design life	5	10	20	50
Total equivalent traffic loading (E80/lane)	3 – 100 million over 20 years	0.3 – 10 million Depending on design strategy	< 3 million Depending on design strategy	< 1 million Depending on design strategy
Typical pavement class[2]	ES10 – ES100	ES1 – ES10	< ES0.03 – ES3	ES0.003 – ES1
Daily traffic (evu)	> 4000	600 – 10 000	< 600	< 500
Riding quality: Constructed IRI Terminal IRI	2.4 – 1.6 3.5	2.9 – 1.6 4.2	3.5 – 2.4 4.5	4.2 – 2.4 5.1
Rut level for flexible pavements (mm) Warning Terminal	10 20	10 20	10 20	10 20
Area of shattered concrete for rigid pavements (%)[3] CRCP and UTCRCP Warning Terminal JCP and DJCP Warning Terminal	0.2 0.5 2 5	0.3 0.7 3 6	0.4 0.8 4 8	0.5 1.0 5 10

Note
1. Although 50% reliability is stated for Category D, this essentially implies designing for an average situation. Great caution should, however, be taken when designing for an average situation with average values.
2. Traffic classes given in Section 4.1.5.
3. These criteria from cncPave.

A similar formula is used to calculate the damage effect of heavy axle load rail cars, which is called the damage factor equation (Zarembski, n.d.). The formula is:

$$Damage\ factor = \left(\frac{P}{P_0}\right)^n$$

where

P = the new axle load,

P_0 = the old axle load, and

n = the damage exponent.

In this model, the rail axle load design ratings used to determine P_0 are based on Figure 3.20. The damage factor is calculated for each tandem axis of a rail wagon and summed together to get the total damage factor per wagon. A similar calculation needs to be done per locomotive and the sum of the damage factors for all locomotives and wagons assigned in the network represents the total rail infrastructure maintenance burden on the economy. A composite damage exponent, based on the weighted average of the damage exponents for the individual rail damage factors (shown in Table 3.22) of 1.959, was used.

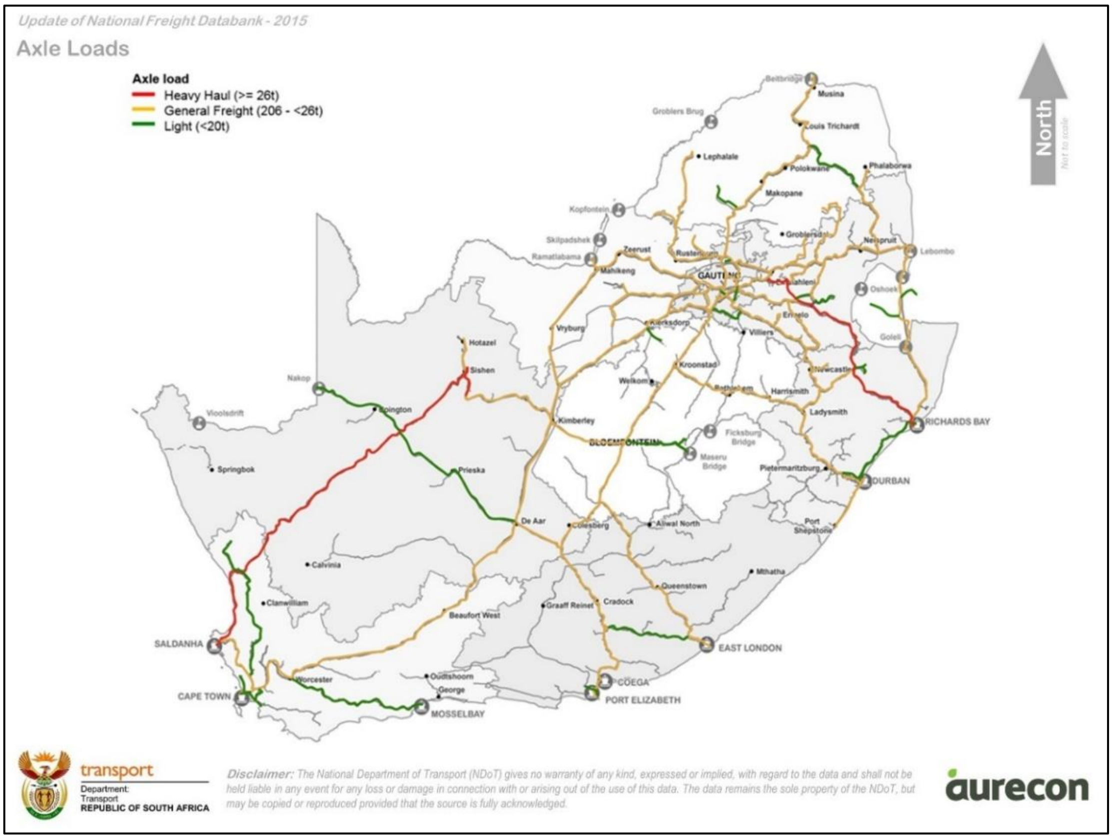


Figure 3.20 South African rail network axle load ratings (http://freightdatabank.info)

The formula is applied to estimate the surface maintenance impact of air freight, in a similar vein. An aircraft classification number (ACN) is a number expressing the relative effect of an aircraft on a pavement for a specified standard subgrade strength and a pavement classification number (PCN) is a number expressing the bearing strength of a pavement for unrestricted operations (Federal Aviation Administration, 2016). The ACN is twice the derived single-wheel load, expressed in thousands of kilograms, with single-wheel tyre pressure standardised at 1.25 megapascals (181 psi) (Federal Aviation Administration, 2014). ACNs and PCNs are used as the new and standard axle loads, respectively. As in the road paving equation, an exponent of 4 is used. The ACN and PCN values for South African airports are shown in Table 3.23.

Table 3.22 Rail heavy axle load damage factors (Zarembski, n.d.; Zarembski, 2015)

	Damage Exponent n	Damage* (per axle)	Damage* (per MGT)
Rail Wear	1	+9%	0%
Rail Fatigue (internal)	3	+29%	+19%
Rail Fatigue (surface)	1.8	+16%	+7%
Rail Joints	3.33	+32%	+21%
Ties	1.5	+13%	+4%
Good Ballast	1	+9%	0%
Poor Ballast	5.6	+60%	+47%
Turnouts	3	+29%	+19%
* Based on 286 000 lb. car.			

Table 3.23 Airport classification numbers used in the case study (Boeing, 2013)

Airport Classification Numbers (ACN)			
Node	**Boeing 737 200**	**Boeing 737 300**	**Hold of Passenger Aircraft**
Bloemfontein	30	33	33
Cape Town	30	33	33
Durban	30	33	33
East London	30	33	33
Gauteng	30	33	33
George	31	35	35
Nelspruit	31	35	35
Port Elizabeth	31	35	35
Upington	30	33	33

ESALs are not, generally, used as a measure of infrastructure maintenance for ports – in this sector maintenance is done as and when needed. Consequently, no ESAL value for the cabotage will be assessed. Little information is available on the maintenance estimates of the hyperloop, but this is not a pavement-based system where loads are transported on a solid surface, so no ESAL value is estimated for this mode.

The ESAL value of each vehicle at each payload (determining the relevant axle loads) is calculated for road, rail and air transport shipments and summed together to determine the total ESAL value for the network assignment in a solution. Both empty return and fully loaded trips' ESAL values are included in the total estimates. The total ESALs per mode are, thus, affected by decision variables GM2, GM6, LM1, LM2, LM3, LM4, LM5 and LM6.

3.3.3 Modelling the social objective

One of the largest problems facing the South African government is wide-spread poverty and unemployment. In the year 2000 the South African Government, along with other members of the United Nations (UN), committed to a national and global plan of action to reduce poverty and ensure the development of its people. This plan was formulated in terms of achieving certain Millennium Development Goals (MDG) over time. Millennium Development Goal number one for South Africa is to eradicate poverty and hunger (Statistics South Africa, 2015a). Policy in South Africa is, generally, made from a pro-poor perspective. It was, thus, decided to use employment as a metric for the social impact of the various transport assignments. The more jobs associated with a solution, the better that solution will be in terms of the social objective, making this objective a maximisation problem.

The social objective is, consequently, measured on a modal level in terms of the number of jobs per mode. The training cost (in Section 3.3.2) is also calculated based on these values. Statistics South Africa (2015b) published statistics on employment in the South African freight transport sector (Figure 3.21) which were used, in conjunction with data in Lane and Vanderschuren (2010b) and Lane (2010), to derive the job-coefficients used in the social objective function calculations, shown in Table 3.24. There is very little information available about the job creation potential of a hyperloop system, but it is known that a high degree of automation is planned. For the case study, a social objective coefficient half of that of rail transport is assumed for a hyperloop system.

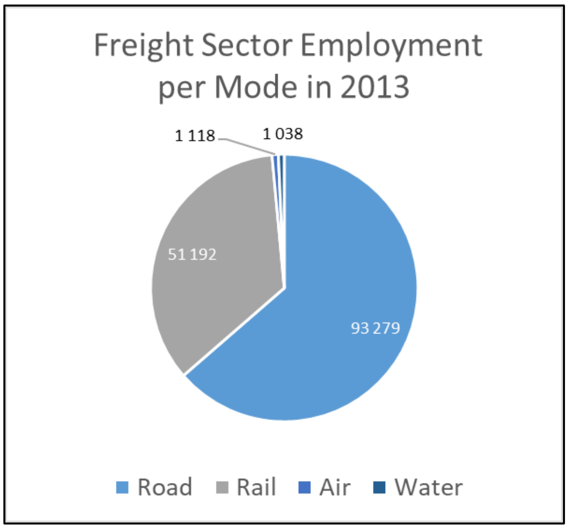


Figure 3.21 South African freight sector employment per mode in 2013 (reworked from Statistics South Africa, 2015b)

Table 3.24 Social objective coefficient

Mode	Jobs/tkm
Road	0.00000030
Rail	0.00000038
Air	0.00000325
Water	0.00000029

The social objective is calculated with the following formula:

$$Social = \sum_{m=1}^{M} (tkm_m \times job\ coefficient_m)$$

where

tkm_m = the tonne-kilometres per mode m (both empty and loaded), $M \in [1, \dots, 5]$, and

$job\ coefficient_m$ = the job coefficient for mode m, $M \in [1, \dots, 5]$.

Decision variables that can affect the total tkm per mode in the network will affect the social objective estimate. These include: GM1, GM2, GM5, GM6, LM1, LM2, LM3, LM4, LM5 and LM6.

3.3.4 Summary of the relationship between the decision variables and objectives

Table 3.25 pairs the assessment criteria with the decision variables that influence their performance.

Table 3.25 Decision variable impacts on the sustainability indicators included in the case study

Decision variables	Decision variable ID	Sustainability indicators						
		Environmental		Economic				Social
		Total energy use	GHG emissions	Capital expenditure	Fuel costs	Maintenance	Taxes	Jobs
Network design	GM1							
Vehicle park restrictions	GM2							
Taxes	GM3							
Driver training	GM4							
New technology	GM5							
Overloading tolerance and enforcement	GM6							
Intermodal/unimodal routing	LM1							
Intramodal split	LM2							
Modal split	LM3							
Route split	LM4							
Vehicle split	LM5							
Vehicle loading regimes	LM6							
Propulsion system split	LM7							
Energy source split	LM8							

3.4 Formulation of the Problem Constraints

Constraints represent any restrictions on the values that the decision variables can assume in the model (Hillier and Lieberman, 2010). Constraints can be either hard constraints, where certain restrictions on the variables have to be enforced and are non-negotiable, or soft constraints, where conditions set on the decision variables are preferences only and do not have to be met. Not meeting a soft constraint typically incurs a penalty in terms of the objective function, thereby encouraging adherence to the soft constraint as far as possible. One of the most common constraint types is boundary constraints. These constraints set the upper and lower limits to the range of values for each decision variable, often delimiting whether both positive and negative values are allowed, or only one of the two. Constraints are also used to indicate what type of values are to be used, for example, whether the variable can take on real or integer or binary values. Another distinction between constraints is whether they are explicit or implicit in the model. Explicit constraints are expressly defined and imposed upon the decision variables, where implicit constraints often result from the definition of the variables themselves, or the relationships between the variables and objectives, as expressed in the objective function.

Stakeholders need to understand and sign off on the constraints applied in any model. Constraints define the boundaries of the model's search space and failure to recognise the impact of constraints on the model's search capabilities and search space can lead to unrealistic expectations or misinterpretation of the results. Constraints have to comply with the limitations set out in the project scoping exercise.

There are only two explicit constraints imposed on the case study model. Because the model centres around the management of energy demand within the freight network, any reduction in energy demand will yield improvements in terms of the many assessment criteria. If left unconstrained, it is conceivable that the model will first try to reduce freight demand as far as possible – if there is no transportation, there will be no energy used. South Africa is a developing country with a struggling economy; the country cannot afford reduced economic activity, making a reduction in freight flows between producers and consumers a non-viable option. The first hard constraint is, thus, that all demand between OD pairs must be met by the network. This constraint aligns with calls in the literature for researching methods of decoupling transport GHG emissions from economic growth. Sims *et al.* (2014) state that: "Decoupling of transport GHG emissions from economic growth needs further elaboration, especially policy frameworks that can enable this decoupling to accelerate in both OECD and non-OECD nations" and that "Reducing global transport greenhouse gas (GHG) emissions will be challenging since the continuing growth in passenger and freight activity could outweigh all mitigation measures unless transport emissions can be strongly decoupled from GDP growth". The second explicit, hard constraint is that demand between the same origin and destination is not allowed, as urban freight is excluded from the model. The detailed definitions of the decision variables included in the case study model (discussed in Section 3.2) provide implicit, hard constraints relative to each variable.

3.5 Identification of Model Parameters

The constants (namely the coefficients) in the constraints and the objective function are called the parameters of the model (Hillier and Lieberman, 2010). The collection of data required for the estimation of the parameters in the case study model serves as an example of the data needed for a tool of this nature. Although stakeholder involvement is not essential during this process, they might prove a valuable resource for reliable data and their ultimate sign-off on the data used as parameters will provide greater confidence in the tool outputs.

Some of the parameters included in the case study have already been mentioned in Sections 3.1 to 3.4. Remaining parameter data is discussed in the remainder of this section.

The total demand for processed foods to be transported between Durban and Gauteng in the model is 1 346 tonnes, of which 86.7% flows from Durban to Gauteng and 13.3% from Gauteng to Durban. The density of each commodity is required to simulate the loading of vehicles. There are variations in the literature about the mean densities of each commodity (for example Van de Reyd and Wouters, 2005 or Robinson, 2013), however, in this model the relative differences in commodity density are more important than being 100% accurate, hence using the values from one source only to ensure this consistency is acceptable. Robinson (2013) published the average density for processed foods as 0.256 tonnes per cubic metre.

Pairing the road vehicles in vehicle park one to processed foods, it is found that tautliners are the body shapes best suited for the case study. Five truck types, thus, remain part of the analysis. A representative vehicle from each type was chosen to base the vehicle characteristics on. These sample vehicles, as well as vehicle parameters, are listed in Table 3.26. Details on the sample vehicles were obtained from the manufacturers' websites and information booklets, a truck transport modelling software solution called TransSolve 2010 (Hellberg Transport Management (HTM), 2010) and two theses on freight transport energy use in South Africa (Thuysbaert, 2008 and Eldestrand and Marin, 2010). It was decided to use a different vehicle manufacturer for each vehicle group, to be more representative of the industry.

The locomotive specifications reworked from Locomotives of South Africa (2018) used in the model are provided in Table 3.27. This indicates the average carrying capacity and tare mass for each locomotive type included in the case study. Rail wagon specifications are shown in Table 4.28, with

Table 3.26 Road vehicle parameters for the vehicle park case study

Vehicle Description			**Vehicle Parameters**		
Vehicle Group	**Sample Vehicle**	**Vehicle Body**	**Maximum Vehicle Weight (kg)**	**Tare Combined Weight (kg)**	**Volumetric Capacity (m^3)**
Rigid Trucks	Isuzu FTR 850	Tautliner	15000	4890	33.2
4x2 truck tractor and 2 axle semi-trailer	Mercedes-Benz ACTROS 2036S/36	Tautliner	31020	9190	37.5
6x4 truck tractor and 2 axle semi-trailer	Powerstar 2642S VX 6x4	Tautliner	43500	14600	89
6x4 truck tractor and 3 axle semi-trailer	Renault C440.26 6x4 TK E6	Tautliner	46500	15233	90
Interlink or drawbar	MAN TGA 26.480 6x4 BLS	Tautliner	56000	26000	120.2

the information obtained from www.spoornet.co.za. Vehicle characteristics for air and water freight are provided in Table 3.29 and Table 3.30, respectively. Information on the air freight carriers were obtained from Boeing.com. A Norwegian feeder container ship served as proxy for the cargo ship. The deadweight tonnage is used as a proxy for maximum payload capacity for water-based freight transport, although this might overstate the payload slightly. Objective function coefficients and other constraint parameters not included in this section will be discussed, as and when appropriate, in the remainder of this document.

Table 3.27 Locomotive characteristics (reworked from Locomotives of South Africa, 2018)

Locomotive Characteristic	**Unit**	**Locomotive Type**						
		Electric Locomotive: Class 10E	**Electric Locomotive: Class 18E**	**Electric Locomotive: Class 14E**	**Electric Locomotive: South African Class Exp AC**	**Electro-Diesel Locomotive: Class 38-000**	**Diesel Locomotive: Class 43-000**	**Diesel Locomotive: Class 36-000**
Average carrying capacity	kg @ 50km/h	2 182 529	1 590 633	2 881 786	1 590 633	423 792	2 118 960	565 056
Tare mass	Tonnes	125	88.9	92.5	85.5	74.74	126	73

Table 3.28 Rail wagon characteristics (reworked from www.spoornet.co.za)

Rail Wagon Type	**Vehicle Parameters**		
	Maximum Payload Capacity (kg)	**Tare Weight (kg)**	**Volumetric Capacity (m^3)**
O-1 Wagon	33 000	26 260	66.3

Table 3.29 Air freight carrier characteristics (reworked from www.Boeing.com)

Air Freight Vehicle	Vehicle Parameters		
	Maximum Payload Capacity	Tare Weight (kg)	Volumetric Capacity (m^3)
Boeing 737 200	13 871	29 810	112
Boeing 737 300	19 731	36 574	130

Table 3.30 Maritime freight vessel parameters (MarineTraffic, 2018)

Cabotage Vessel	Vehicle Parameters		
	Deadweight Tonnage (t)	Tare Combined Weight (t)	Volumetric Capacity (m^3)
Cargo ship	5 202	1 734	78 000

3.6 Assumptions in the Problem Formulation

A mathematical model is only intended to be an idealisation of the real problem (Hillier and Lieberman, 2010). As such, approximations and simplifying assumptions are generally required in order for the model to be tractable. Adding too much information can make the model too unwieldy for useful analysis of the problem, when all that is really needed is that there be a reasonably high correlation between the prediction of the model and what would actually happen in the real problem (Hillier and Lieberman, 2010).

Chapter 3 has indicated that the tool requires a lot of data; scaling up the tool to a real-world application will require even greater volumes of data. For this reason, assumptions simplifying the relationship between elements in the network, or simplified proxies for data, needs to be included in the model. It is imperative to be transparent and forthcoming about the data used in the model, as well as any assumptions or simplifications made. Stakeholder sign-off and participation in the development of assumptions is required for the model results to be accepted.

3.7 Chapter Summary

Upon completion of the problem formulation phase, a clear and concise picture of what is to be modelled should exist, unambiguously delineating what is included and what is excluded from the analysis. The value and nature of stakeholder input has been discussed throughout this chapter. Assumptions framing the decision context and model outputs have been clearly identified and explicitly noted. The chapter provides an outline of the typical variables, assessment criteria, constraints and parameters needed for a decision support tool in this context and a detailed inventory of the values included in the case study tool is provided.

Four research questions have been addressed in this chapter. First, question 2.1 (how to convert freight energy management measures and policies into decision variables) is addressed in Sections 3.2 and 3.4. Secondly, question 2.10 (how to convert sustainability assessment indicators into objective functions) is answered in Section 3.2.16, while question 2.14 (what constraints should be included and are they implicitly or explicitly modelled) is addressed in Section 3.4. Question 2.15 (what are the data requirements of the tool) is answered throughout the entire chapter. Additional data required is also mentioned, when appropriate, in Chapters 4 and 5.

The problem formulation step in the operations research process is one of the longest, slowest and most labour-intensive steps. This is mainly due to data collection efforts requiring a lot of manpower and because workshopping the model scoping and definition and formulation of variables, assessment criteria, constraints and parameters with stakeholders and decision-makers can be an iterative and time-consuming process. Ultimately, though, spending the effort on this step ensures model usefulness and acceptance and saves time on the modelling front by providing modellers with a clear scope and brief on what to model.

4 Deciding on a Modelling Tool

Following the formulation and exploration of the problem (as discussed in Chapter 3), a mathematical representation of the problem is developed. Once this mathematical formulation is known, the best tool or technique to find a solution to the problem can be identified. This corresponds to step three of the standardised operations research process. If the mathematical relationships required are too complex to allow the determination (or formulation) of an analytic solution, the operations researchers may opt to simplify the model and use a heuristic approach, or the researchers may consider the use of simulation, if appropriate (Taha, 2003). In some cases, a combination of mathematical, simulation and heuristic models may be needed to formulate and solve the decision problem. This chapter explores the identification of the most apt modelling tool to use.

4.1 Modelling Tool Requirement Specification

The premise underlying this research is that freight transportation should be managed with sustainability as the end goal and that there are decisions in terms of freight transport energy management, whose overall sustainability impacts are preferred over others. Figure 4.1 illustrates this concept graphically. Any solution in one of the three sustainability spheres will have a positive impact, however, a solution in an area where two spheres overlap will be beneficial on two fronts and, thus, preferred over a singularly impactful solution. The logical conclusion is to aim for solutions that reside in the centre of the graph, where all three sustainability impacts are affected positively.

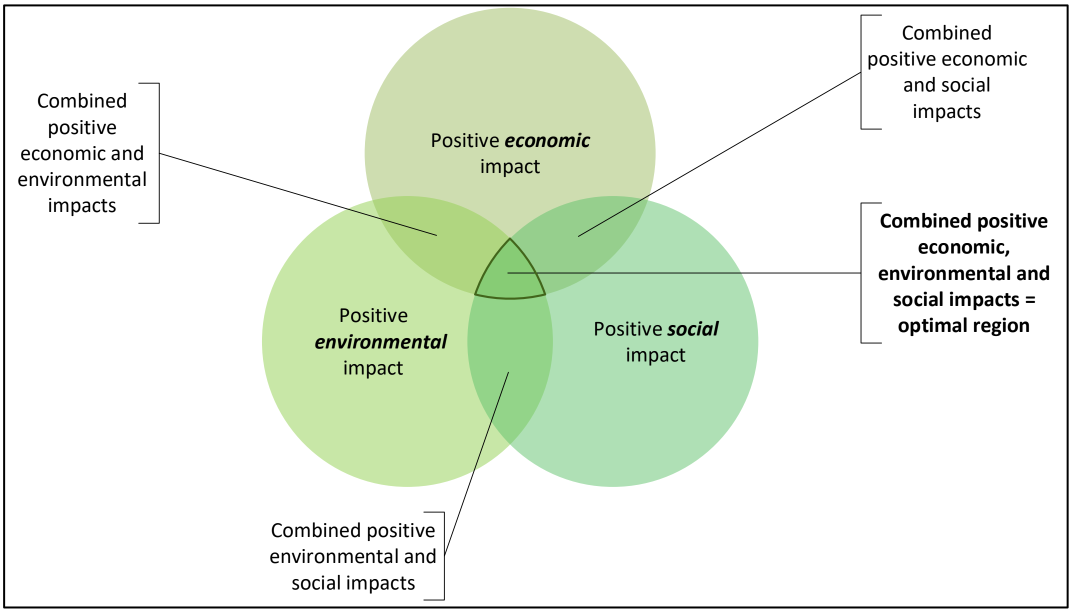


Figure 4.1 Conceptual illustration of the existence of preferred solutions

There are various ways and means in which the system can be altered to improve sustainability in one aspect, but the impact of such alterations can also be negative for some other sustainability aspects. This is because the sustainability objectives are not independent - there are conflicts between the three pillars of sustainability and trade-offs and compromises have to be made in order to find holistically acceptable solutions. Essentially, the decision support tool developed needs to propose system alterations, or a portfolio of system alterations, that achieve improvements in some sustainability respects, whilst maintaining balance between all other sustainability aspects. It is important to consider what such a quantitative energy management measure package selection process (conceptually depicted in Figure 4.2) would comprise.

First, assume that measures can only be implemented and impact the transport system in a singular known and fixed manner, i.e. no variability in terms of measure implementation or impact is allowed. Then, let M_{ij} represent a binary variable set to one, if energy management measure i is included in measure package j. $i \in [1, n]$ and $j \in [1, m]$ where n denotes the number of energy management measures (a.k.a. decision variables) and m the number of combinations of decision variables considered. If measure i is not included in measure package j, the value of M_{ij} is equal to zero. Let P_j denote a unique combination (package) of all the measures, regarded as the vector of measures $P_j = < M_{1j}, M_{2j}, M_{3j}, \dots, M_{nj} >$. For example, if $n = 5$, $P_4 = < 1,0,1,0,0 >$ in Figure 4.2. Measure package four, thus, consists of the implementation of measures one and three, only.

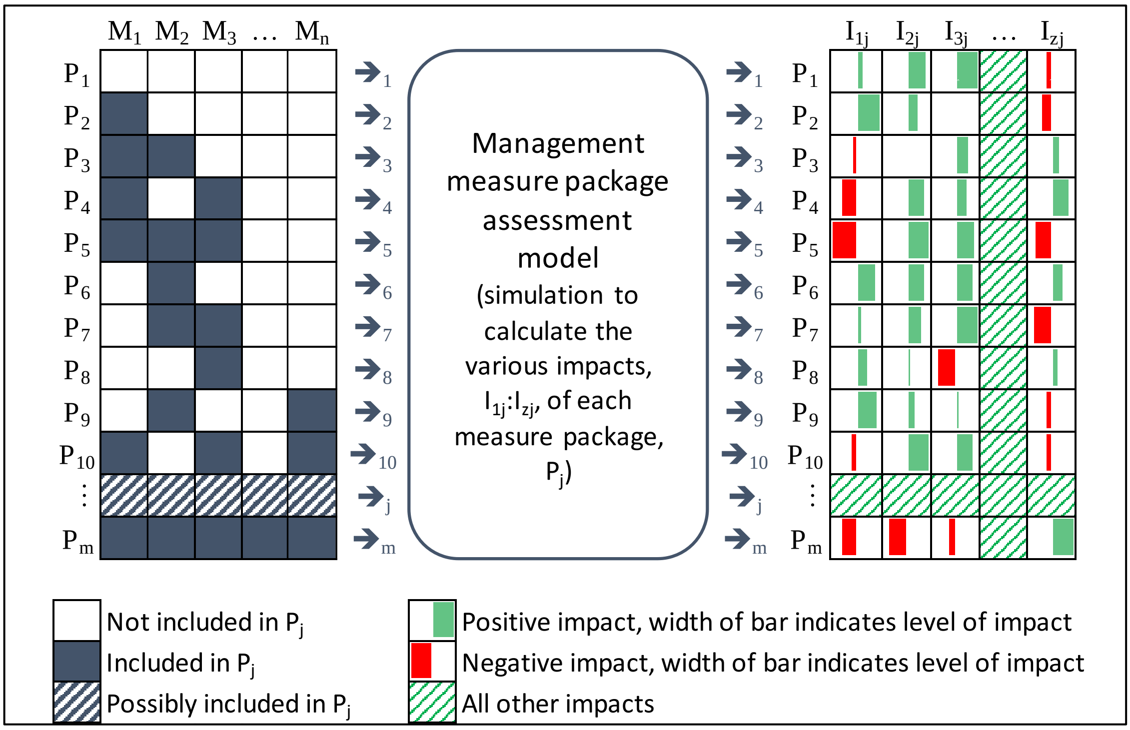


Figure 4.2 Conceptual model of an energy management measure package assessment process

Assuming there is only a fixed number of packages that can be formed, once all the measure package combinations have been formulated, each package needs to be evaluated with some form of package assessment model. These assessments typically calculate the cumulative impact of all measures included in a package on various predefined criteria. Let I_{kj} denote the total impact of measure package j on criteria k, where $k \in [1, z]$ and z represents the total number of criteria to be considered. I_{kj} can take on positive or negative values. The outputs of the assessment model can then be used to sort and filter measure packages and can serve as input to a multi-criteria decision-making process where preferred packages can be identified and selected.

The effort and time involved with the generation of the assessment output scores is directly proportionate to the number of measure packages that need to be evaluated, as well as the complexity of the assessment function. The number of measure combinations (packages) that need to be assessed is, in turn, dependent on the number of measures available for consideration and can be calculated by 2^n. Hence, if there are five measures to consider, there will be $2^5 = 32$ measure packages to assess ($m = 32$). If the assumption that measures can only be implemented and impact the transport system in a singular, known and fixed manner, is relaxed, the size of the problem grows exponentially. For instance, if measure one can be implemented in three distinct ways, as opposed to only one way, two new measures are essentially added and need to be considered. This implies that 128 packages will have to be assessed ($2^{5+2} = 128$). Should all five measures be allowed to have three discrete implementation alternatives, the number of policies to be assessed increases to 32 768 options ($2^{5\times3}$). The assessment model will already be facing a daunting task, and this is with only five discrete measures to consider. When studying the literature on the topic (see Section 1.1), it is found that there are hundreds of viable, researched and published potential energy management measures worthy of consideration. It can, thus, be expected that quite a large search space will have to be explored by such a tool.

The 14 decision variables included in the case study model would yield a search space of 16 384 solutions if each variable could only be implemented in one way. From the decision variable declaration in Section 3.2, it is known that certain measures need to be modelled as continuous variables (in other words, measures can be implemented to any extent). This yields an infinite number of measure packages that can be formulated and that need to be assessed. The search space explodes and becomes infinitely large, and this is still a simplified version of the problem.

The decision variables are not all completely independent variables, adding further to the problem complexity. All the government measures (GM1 to GM6), as well as logistics measures one (LM1) and six (LM6), are independent measures. This means that their values in the model are set completely independent to the value of any of the other decision variables. LM2, LM3, LM4, LM5, LM7 and LM8, on the other hand, are dependent variables, meaning that decisions made on the variables they are dependent on will determine the range of decisions that can be made with regards to these dependent variables. For example, the decision made in terms of the vehicle park selected (GM2) influences the vehicle split decision variable (LM5) by limiting the range of vehicles to split the demand between. This, in turn, affects the decision on propulsion system split (LM7), which affects the energy source split decision (LM8). LM8 is dependent on LM7, LM7 (and, thus, LM8) on LM5 and LM5, LM7 and LM8 on GM2. Table 4.1 displays the dependencies between the decision variables included in the case study model. The decision variables in each column are dependent on the decision variables in the row corresponding to each highlighted cell.

Table 4.1 Dependencies between decision variables in the case study

Decision Variable		**Intermodal or Unimodal Routing**	**Intramodal Split**	**Modal Split**	**Route Split**	**Vehicle Split**	**Vehicle Loading Regimes**	**Propulsion System Split**	**Energy Source Split**
		LM1	LM2	LM3	LM4	LM5	LM6	LM7	LM8
Network Design	GM1								
Vehicle Park Restrictions	GM2								
Taxes	GM3								
Driver Training	GM4								
New Technology	GM5								
Overloading Tolerance and Enforcement	GM6								
Intermodal or Unimodal Routing	LM1								
Intramodal Split	LM2								
Modal Split	LM3								
Route Split	LM4								
Vehicle Split	LM5								
Vehicle Loading Regimes	LM6								
Propulsion System Split	LM7								
Energy Source Split	LM8								

A sequence emerges in which the decisions on the dependent variables need to be made. The sequence followed in the case study model is graphically illustrated in Figure 4.3. LM1 (unimodal or intermodal transport) is determined first and, based on the decision made, one of two decision sequences follow – a unimodal sequence and an intermodal sequence. In the unimodal sequence, LM3 (the modal split) is determined next, followed by LM2 (intramodal transport allowance). Depending on the decision made in LM2, the sequence either reverts to the intermodal sequence (if intramodal transport is selected) or remains in the unimodal sequence. The next decision in the unimodal sequence is LM4 (the route split), followed by LM5 (the vehicle split), LM7 (the propulsion system split) and LM8 (the energy source split). If the intermodal sequence is followed, LM4 (the route split) occurs next. This routing decision imposes a modal split based on the modes associated with the route segments included in each route. No explicit decision is made on LM3 (modal split) in the intermodal sequence, however. Once the route split has been determined, the sequence is the same as for the unimodal sequence, i.e. LM5 followed by LM7 and LM8, respectively.

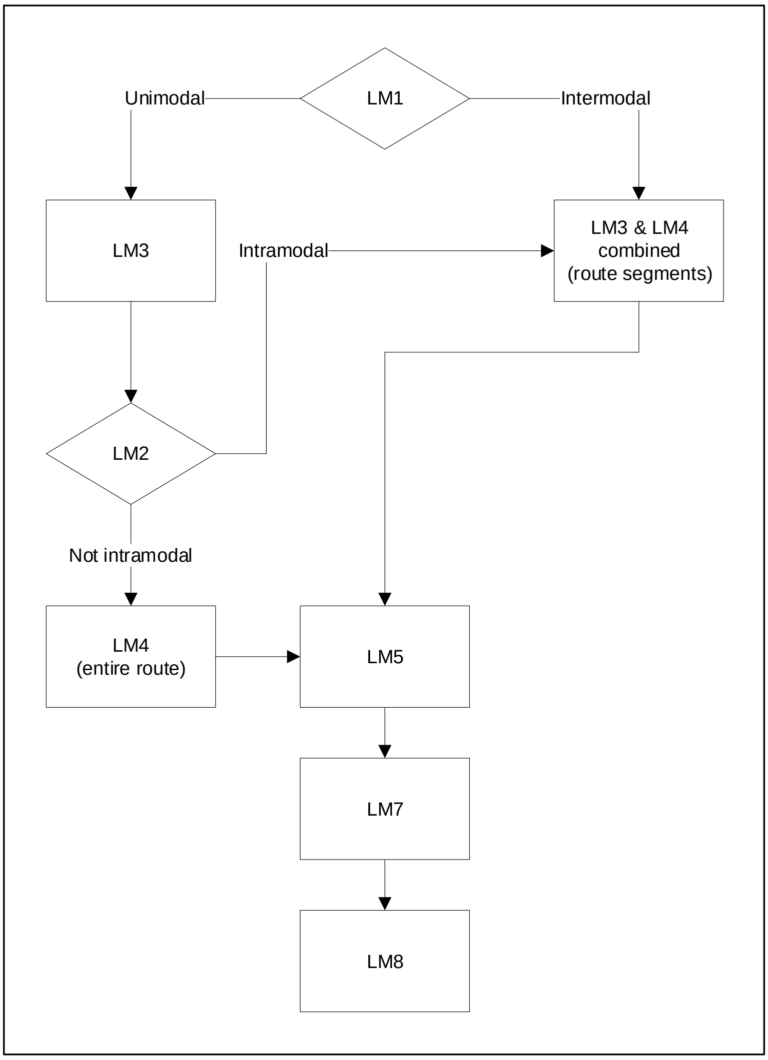


Figure 4.3 Sequence of decisions for dependent decision variables in the case study

In addition, there is dimensionality to be accounted for in terms of the decision variables. A unique and independent value is assigned to each decision variable for each dimension of the variable. The dimensionality of the variables in the case study model are shown in Table 4.2. The values in brackets in Table 4.2 indicate the maximum number of potential alternatives per dimension in the case study model. Directionality is important in terms of flows between OD pairs, hence Durban to Gauteng and Gauteng to Durban are regarded as two independent OD pairs. Decision variables GM1 to GM6, as well as LM6, are given unique values once per solution. These variables, thus, have a dimensionality of one. LM1 will be assigned a unique value for each commodity and each OD pair in the model. Because there is only one commodity considered in the case study, LM1 has a dimensionality of two (meaning a unique value will be assigned for each OD pair). The decision sequence dependent on LM1 (Figure 4.3) will have to be repeated for each dimension of LM1.

Table 4.2 Dimensionality of the decision variables in the case study

Decision Variable	Decision Variable ID	Dimensionality of the Decision Variables						
		Per Solution (1)	Commodity (1)	OD Pair (2)	Mode (5)	Route/ Segment (3)/(182-186)	Vehicle Type (5)	Propulsion System (2)
Network design	GM1							
Vehicle park restrictions	GM2							
Taxes	GM3							
Driver training	GM4							
New technology	GM5							
Overloading tolerance and enforcement	GM6							
Intermodal/unimodal routing	LM1							
Intramodal split	LM2							
Modal split	LM3							
Route split	LM4							
Vehicle split	LM5							
Vehicle loading regimes	LM6							
Propulsion system split	LM7							
Energy source split	LM8							

If a unimodal sequence is to be followed, LM3 will also have a dimensionality of two and LM2 a maximum potential dimensionality of ten (a decision will be made for each mode, for each OD pair and commodity combination). In this sequence, LM4 will also have a maximum dimensionality of ten. LM5's maximum potential dimensionality equals thirty, because a vehicle split decision only has to be made once per route (and remains valid for each segment of the route) and there is a maximum of three routes per mode. The maximum potential dimensionality of LM7 is 150 and 300 for LM8 in the unimodal sequence. Summing up over all decision variables, the maximum potential number of decisions to be made when following the unimodal sequence equals $7 + 2 + 2 + 10 + 10 + 30 + 150 + 300 = 511$ in the case study model.

If a purely intermodal sequence is followed, there is no explicit decision to be made in terms of LM2 or LM3. LM4 needs to be determined twice, once for every decision of LM1. Again, three routes are developed, but, because the routes are now intermodal or intramodal in nature, further transport assignment decisions need to be made for each segment of the route individually, based on the segment characteristics. The case study network comprises between 182 and 186 segments (depending on decisions made in terms of GM1 and GM5). LM5 could, thus, potentially have a decision dimensionality of $186 \times 2 = 372$. Similarly, LM7 has a maximum potential dimensionality of $5 \times 372 = 1\,860$ and LM8 of $2 \times 1\,860 = 3\,720$. The total number of decisions increase to $7 + 2 + 2 + 372 + 1\,860 + 3\,720 = 5\,963$. The cells highlighted with the diagonal pattern in

Table 4.2 indicate dimensionality values dependent on the decision made in LM1, i.e. that vary based on whether a unimodal or intermodal sequence is followed.

It is important to note that decisions on LM1 and LM2 can vary for each decision dimension, so the actual number of decisions per model run will lie somewhere within the range of 511 and 5 963 per solution. A solution (or package of measures) is, thus, a unique combination of up to 5 963 decisions which result in the freight demand allocation values that are used to calculate the performance of the solution in terms of the three objectives.

Given all these layers of complexity, developing and exhaustively searching through all the potential decision measure packages is impossible. The search space is infinite, rendering enumerative or manual search procedures unsuitable. Ranking procedures, where a finite set of alternatives are compared to each other, is only useful once a finite list of (good) alternative options has been developed. The decision support tool developed for this problem will be of great value if it can assist in the formulation and demarcation of such a list of alternatives. In order to reduce the search space to such a set of solutions, the tool needs to be able to simultaneously evaluate alternatives over multiple criteria, expressed in different units of measurement, and adequately explore the entire search space. Additionally, solutions need to be developed preserving the sequential and dimensional integrity of the decision variables, taking their interdependencies into account.

4.2 Overview of Modelling Tools

Numerous modelling tools have been developed over the years to assist decision-making. Segura *et al.* (2014) categorise decision support systems into six main approaches: multiple criteria decision-making, optimisation modelling, simulation modelling, statistical methods, economic modelling and information systems. Table 4.3 lists a number of operations research models and methods that can be used with each approach.

Multi-criteria decision-making (MCDM) is a general framework for supporting complex decision-making situations with multiple, and often conflicting, objectives that stakeholder groups and/or decision-makers value differently (Saarikoski *et al.*, 2016). It is a tool used to evaluate and compare a finite list of alternative options over diverse and uncorrelated criteria (which can include both quantitative and qualitative elements) in order to aid decision-makers in selecting a preferred cause of action.

Optimisation methods, in turn, refers to the study of decision problems in which the modeller seeks to minimise or maximise a function by systematically choosing the values of variables within their

Table 4.3 Decision support system models and methods classified by approach (Segura et al., 2014)

Models and Methods	
Multiple Criteria Decision Making	Analytic Hierarchy Process (AHP), Goal Programming, Multi-Attribute Value (MAV), Multi-Attribute Utility Theory (MAUT), Multi-Attribute Function, Multi-Criteria Analysis (MCA), Preference Ranking Organisation Methods for Enrichment Evaluations (PROMETHEE), Simple Multi-Attribute Rating Technique (SMART), Stochastic Multicriteria Acceptability Analysis (SMAA), Group Decision Making and Voting Techniques
Optimization models	Dynamic Programming (DP), Graph Theory, Heuristics, Linear Programming (LP), Mathematical Programming (MP), Mix Integer Programming (MIP), Non-Linear Programming (NLP) and Optimization (without specific methods)
Simulation models	Dynamic Modeling, Growth Models (GM), Monte Carlo Simulation Method (MCSM), Simulation Models (without specific methods), Risk Model and Yield Models
Statistical methods	Bayesian Method, Data Mining, Fuzzy/Neural System, Least Squared Method, Logistic Regression (LR), Multivariate Model, Regression Analysis (RA), Statistical Models (without specific techniques), Stochastic Models and ANalysis Of VAriance (ANOVA)
Economic models	Cost-Benefit Analysis (CBA), Gap Model, Economic Accounting, Economic Models and Strengths, Weaknesses, Opportunities and Threats (SWOT) Analysis
Information Systems	Database Management System (DBMS), Relational Database Management System (RDBMS) and Geographic Information System (GIS)

allowed sets (Zhang *et al.*, 2015). "Mathematical optimisation may be described as the science of determining the best solutions to mathematically defined problems, which may be models of physical reality or of manufacturing and management systems. In the first case, solutions are often sought that correspond to minimum energy configurations of general structures, from molecules to suspension bridges and are, therefore, of interest to science and engineering. In the second case, commercial and financial considerations of economic importance to society and industry come into play and it is required to make decisions that will ensure, for example, maximum profit or minimum cost" (Snyman, 2005).

Optimisation models represent problem choices as decision variables and seek values that maximise or minimise objective functions of the decision variables, subject to constraints on variable values expressing the limits on possible decision choices (Rardin, 1998; Winston, 2004; May *et al.*, 2005). Traditionally, the best decision was determined by the identification of a possible solution, testing it, appraising it and then seeking improvements. However, this process can be inefficient, as time is wasted on testing inappropriate strategies and there is no guarantee that the best strategy will be found (May *et al.*, 2005). The benefits of optimisation modelling are in developing more effective strategies to find the best solution and doing so more rapidly. Optimisation is a very elegant way of choosing the best strategy, whilst also producing interesting new strategies that might not otherwise have been thought of (May *et al.*, 2005). A key feature of optimisation models is that the model generates the solutions, not the modeller.

Numerical search is the process of systematically trying different choices for the decision variables, whilst keeping track of the feasible one with the best objective function value found so far (Rardin, 1998). Inferences from a numerical search are limited to the specific points explored, unless mathematical structure in the model supports further deduction. Most optimisation algorithms are developed based on a numerical search premise, although searches are performed in an intelligent fashion in order to prove optimality, or to provide high confidence levels in the near optimality of the proposed solutions. Any specification of the decision variables that satisfies all of the model's constraints is said to be in the "feasible region". An optimal solution to an optimisation model is any point in the feasible region that optimises the objective function (Winston, 2004). It is possible that there can be multiple optimal solutions.

When the problem complexity is too high to find an exact optimal solution, operations research teams occasionally use only heuristic procedures (i.e. intuitively designed procedures that do not guarantee an optimal solution) to find a good sub-optimal solution (Hillier and Lieberman, 2010). In recent years, great progress has been made in developing efficient and effective metaheuristics that provide both a general structure and strategy guidelines for designing a specific heuristic procedure to fit a particular kind of problem (Hillier and Lieberman, 2010). "However, in spite of the proliferation of optimisation methods, there is no universal method for solving all optimisation problems. According to Nocedal and Wright (1999): there are numerous algorithms, each of which is tailored to a particular type of optimisation problem. It is often the user's responsibility to choose an algorithm that is appropriate for the specific application. This choice is an important one; it may determine whether the problem is solved rapidly or slowly and, indeed, whether the solution is found at all" (Snyman, 2005).

Multi-objective programming (MOP) is the process of simultaneously optimising two or more conflicting objectives, subject to certain constraints (Zhang *et al.*, 2015). MOP problems can be found wherever optimal decisions need to be made in the presence of trade-offs between two or more conflicting objectives. In general, a multi-objective programming problem should not have a single solution that simultaneously minimises or maximises each objective to its fullest. In each case an objective must have reached a point such that, when attempting to optimise the objective further, other objectives suffer as a result. Finding such a solution and quantifying how much better this solution is compared to other solutions, is the goal when setting up and solving a multi-objective optimisation problem (Zhang *et al.*, 2015). Zhang *et al.* (2015) proclaim that optimisation is an ideal model for decision-making, with the single limitation that it only works if the problem is structured and, generally, deterministic.

In single-objective optimisation, there is only one global optimum, but in multi-objective optimisation (MOO), there is a set of solutions, called the Pareto-optimal (PO) set, in which all the solutions are considered to be equally important and all of which constitute global optimum solutions (Bandyopadhyay *et al.*, 2008). MOO can be formally stated as follows: find the vectors $\bar{x}^* = [x_1^*, x_2^*, \dots, x_n^*]$ of decision variables that simultaneously optimise the *M* objective values $\{f_1(\bar{x}), f_2(\bar{x}), \dots, f_M(\bar{x})\}$, while satisfying the constraints, if any (Bandyopadhyay *et al.*, 2008). An important concept of MOO is that of domination. A solution is said to dominate another solution if it performs at least as good in terms of all the objectives, but is strictly better in at least one of the objectives. In the context of a maximisation problem, a solution $\overline{x_i}$ is said to dominate solution $\overline{x_j}$ if $\forall k \in 1,2, \dots, M,\ f_k(\overline{x_i}) \geq f_k(\overline{x_j})$ and $\exists k \in 1,2, \dots, M$ such that $f_k(\overline{x_i}) > f_k(\overline{x_j})$. Among a set of solutions *P*, the non-dominated set of solutions P' are those that are not dominated by any member of the set *P*. The non-dominated set of the entire search space *S* is known as the Pareto-optimal set (Bandyopadhyay *et al.*, 2008).

Simulation modelling refers to a broad collection of methods and applications to mimic the behaviour of real systems (Kelton *et al.*, 2004). It is the process of designing and creating a computerised model of a real or proposed system, for the purpose of conducting numerical experiments to give a better understanding of the behaviour of that system for a given set of conditions. “Although it can be used to study simple systems, the real power of this technique is when we use it to study complex systems”. Where there are high levels of complexity, fewer simplifying assumptions are needed to enable analysis when compared to other methods.

The underlying premise of any simulation model is to take inputs, transform them according to predefined rules and processes, producing the resultant outputs (Figure 4.4). A simulation model can be used to compare and contrast a fixed set of alternative system configurations with a high degree of tractability and transparency, despite accounting for complex relationships within the system. Simulation models often possess high validity, because they track true system behaviour fairly accurately (Rardin, 1998).

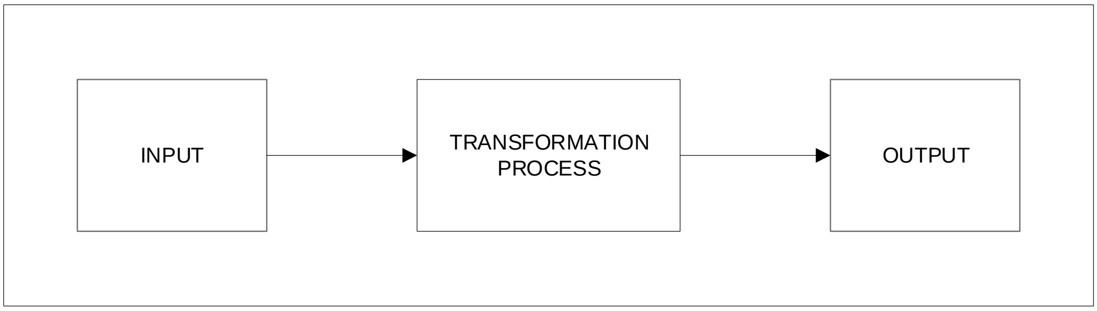


Figure 4.4 Conceptual diagram of a simulation model

A tool that is often used to support decision-making, is economic modelling, where the monetary impacts of various predefined alternatives are determined and compared to each other. Economic models generally convert all impacts (both positive and negative) into monetary values in order to tally impacts on a coherent scale. In many real-world situations the assumptions required for this conversion numbs some of the characteristics of the problems and can be highly inaccurate or even impossible to fairly determine.

Statistical methods are typically used to explore relationships and patterns in data and to develop forecasting models. Decision-makers can use this new information as inputs to the decision-making process, but these methods are generally used as underlying support tools to ensure the adequate handling of data used in simulation or optimisation models, or MCDM situations. Information systems are generally also used in a similar vein – more as a tool to generate supporting information than as a decision aid by itself. Analyses using geographical information systems (GIS) can, however, be seen as a form of simulation modelling in the right context.

Decisions sometimes have to be made in environments fraught with uncertainty. Decision analysis (utilising, for example, decision trees, statistical methods and utility theory) is designed to address this type of decision-making (Hillier and Lieberman, 2010). Here, external factors beyond the decision-maker's control greatly influence the decision and need to be specifically accounted for. Decision trees are often helpful in situations of multi-stage decision problems for choosing best practices and can be applied to assist individuals in choosing from among many best practices (Frey and Kuo, 2007). A decision tree involves a hierarchical cascade of questions to guide the decision-maker toward promising best practices appropriate to their situations. “Although such a logical and temporal structuring of decision-making is quite useful and instructive for dealing with simple problems, it is not adequate for dealing with complexity” (Zeleny, 1982).

4.3 Tool Identification

By marrying the modelling tool specification developed in Section 4.1 with the tool options discussed in Section 4.2, the appropriate modelling tool for the decision support system developed in this dissertation can be identified. The crux of the matter is that there is an infinite search space (feasible region) to navigate and computerised assistance is needed with this. Assistance is needed in managing to search through the entire space in a non-labour-intensive way. Put differently, a quantitative model able to deal with an infinite search space, in a reasonable amount of time, with reasonable confidence in the results, is needed. Additionally, the model needs to be prescriptive, instead of descriptive. Prescriptive models prescribe behaviour for organisations that will enable it to best meet its goal(s) (Winston, 2004). Models that evaluate fixed decision alternatives, rather than indicating good choices, may be termed descriptive models (Rardin, 1998). Descriptive models yield fewer analytical inferences than prescriptive models, because they take both input parameters and decisions as fixed. Optimisation models are prescriptive models, while simulation models are examples of descriptive models.

Optimisation techniques can be used to find optimal, or near optimal, portfolios of freight energy management measures (of which there may be multiple variants). More specifically, metaheuristic search algorithms are appropriate tools for use in this case, as they can deal with infinite search spaces and, although there are no guarantees of absolute optimality, there can be a high level of confidence in the results. Enumeration is not compatible with continuous variables, as there are an infinite number of potential solutions to enumerate, which would take an infinite amount of time. If the use of continuous variables is exchanged for the use of discrete step sizes to enumerate, a sufficient processor might be able to produce a definitive result, but the determination of the step size is a potential pitfall. If the step size is too small, the model will still take an impractically long time to run and produce a result. Conversely, if the step size is too large, the optimal solution might be overlooked. There is no way of determining whether or not the optimal solution has been found, nor will the model have the freedom to explore the area around a promising solution in greater detail (where a metaheuristic will have this ability). In this case, where the certainty advantage of enumeration has been removed, metaheuristics are a better approach.

Multi-objective optimisation algorithms and metaheuristics exist and can be applied to accommodate the multiple objectives of the problem at hand. However, simulation modelling is the most appropriate tool to analyse the impact of decisions within the freight sector, as simulation can accommodate the scale and complexity required to model the network assignment of freight transport demand in a transparent, robust and accurate manner. Enforcing the decision sequence, dependencies between variables and the dimensionality of decisions firmly resides within the domain of simulation modelling.

A combination between multi-objective optimisation and simulation (called simulation optimisation) will be able to provide the most accurate representation of the freight system assignment and its consequent impacts on the objectives, whilst being able to effectively explore the decision space. Finding a reduced set of optimal solutions will provide the information necessary for decision-makers to steer the freight transport sector towards true sustainability.

Simulation optimisation is the integration of optimisation and simulation techniques. When the goal is to find the optimal value for input variables in terms of the system outcomes in a simulation, one approach would be to run simulation experiments for all possible input variables. However, this approach is not always practical, for example there might be too many possible values for input variables, or the simulation model might be too complicated and expensive to run for sub-optimal input variable values. The process of finding the best input variable values from among all possibilities without explicitly evaluating each possibility, is called simulation optimisation (Carson and Maria, 1997). The objective of simulation optimisation is minimising the resources spent, while maximising the information obtained in a simulation experiment.

A general simulation model comprises *n* input variables $(x_1, x_2, \dots, x_n)$ and *m* output variables $(y_1, y_2, \dots, y_m)$, as depicted in Figure 4.5 (Carson and Maria, 1997). Simulation optimisation entails finding optimal settings of the input variables, i.e. values for $x_1, x_2, \dots, x_n$ which optimise the output variable(s). Figure 4.6 is a conceptual diagram of a simulation optimisation model. The output of a simulation model is used by an optimisation strategy to provide feedback on progress of the search for the optimal solution. This, in turn, guides further input to the simulation model (Carson and Maria, 1997).

Carson and Maria (1997) define six major categories of simulation optimisation methods: gradient based search methods, stochastic optimisation, response surface methodology, heuristic methods, A-teams and statistical methods. Jalali and van Nieuwenhuyse (2015) found that the different simulation

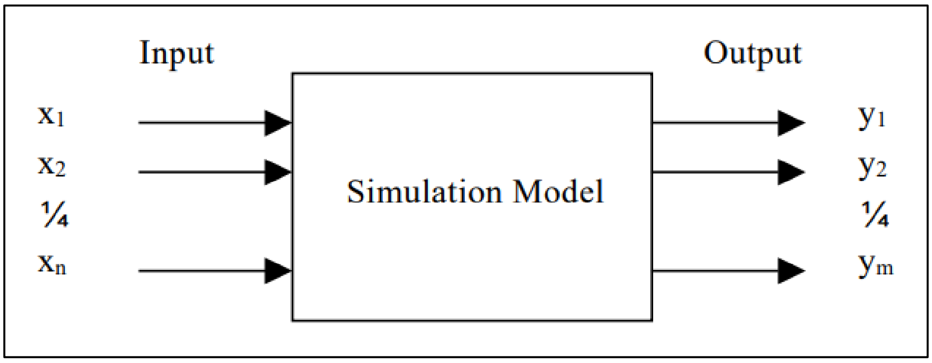


Figure 4.5 Formulation of a simulation model (Carson and Maria, 1997)

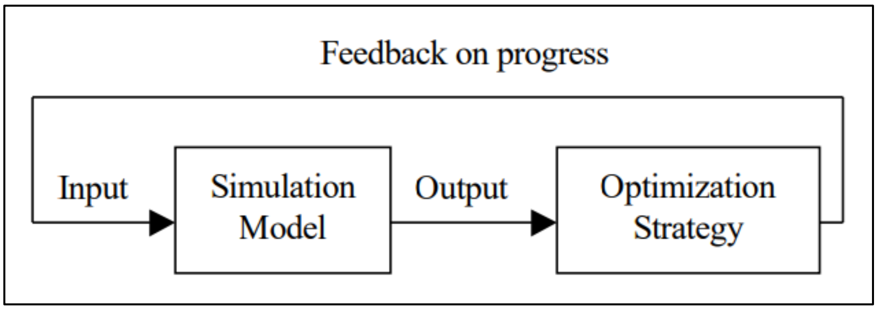


Figure 4.6 A simulation optimisation model (Carson and Maria, 1997)

optimisation methods can be categorised according to whether the decision variables are discrete or continuous. Their categorisation is shown in Figure 4.7.

When decision variables are discrete and the feasible set is finite and small (at most a few hundred feasible solutions), both multiple comparisons and ranking and selection can be used. When the feasible set is very large (or even infinite), metaheuristic methods are popular. Examples of metaheuristics include genetic algorithms, tabu search, simulated annealing and particle swarm optimisation. When the decision variables are continuous, most discrete simulation optimisation techniques become unsuitable, because the number of feasible solutions is infinite (Jalali and Van Nieuwenhuyse, 2015). As shown in Figure 4.7, gradient-based methods (e.g., stochastic approximation, sample path optimisation) are appropriate when the objective function is differentiable. Metamodel and metaheuristic methods, in contrast, do not require differentiability of the objective function. Jalali and van Nieuwehuyse (2015) conclude that metaheuristics (especially genetic algorithms) and methods that combine several simulation optimisation techniques are the most popular.

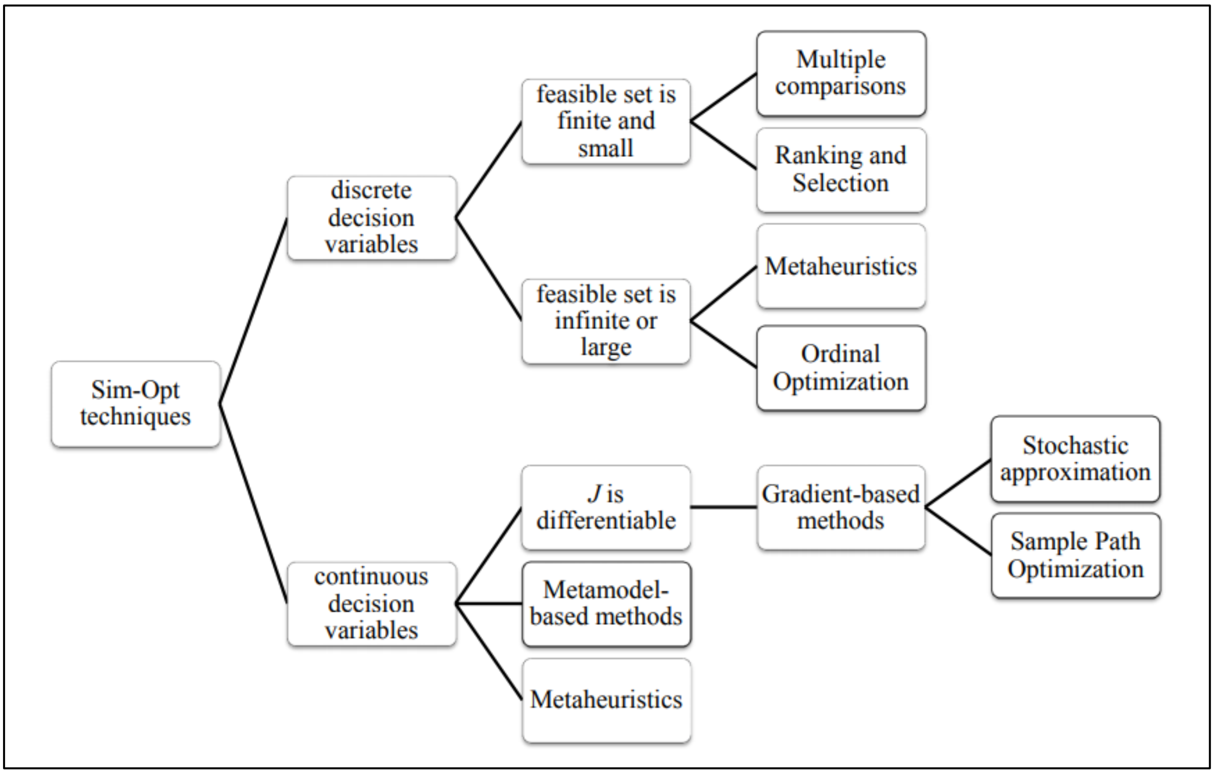


Figure 4.7 Categorisation of simulation optimisation techniques (Jalali and Van Nieuwenhuyse, 2015)

Table 5.4 summarises the performance of the tools considered thus far in terms of the desirable properties of the tool, as described in Section 4.1. The table shows that metaheuristic simulation optimisation combines the diverse strengths of multi-objective optimisation, simulation and metaheuristics, rendering this the preferred modelling tool for the decision support system developed in this dissertation.

Metaheuristics are general algorithmic frameworks, often nature-inspired, designed to solve complex optimisation problems. They are emerging as successful alternatives to more classical approaches for solving optimisation problems that include, in their mathematical formulation, uncertain, stochastic and dynamic information (Bianchi *et al.*, 2009). A metaheuristic is a higher-level procedure (heuristic) designed to find, generate, or select a heuristic (partial search algorithm) that may provide a sufficiently good solution to an optimisation problem, especially with incomplete or imperfect information, or limited computation capacity. Metaheuristics sample a set of solutions which is too large to be completely sampled. Compared to optimisation algorithms and iterative methods, metaheuristics do not guarantee that a globally optimal solution can be found on some classes of problems (Blum and Roli, 2003). A well-designed heuristic can, however, usually provide a solution that is at least nearly optimal or conclude that no such solutions exist (Hillier and Lieberman, 2010). “A metaheuristic is a general kind of solution method that orchestrates the interaction between local improvement procedures and higher-level strategies to create a process that is capable of escaping from local optima and performing a robust search of a feasible region" (Hillier and Lieberman, 2010).

Many metaheuristics implement some form of stochastic optimisation, so that the solution found is dependent on the set of random variables generated (Bianchi *et al.*, 2009). In combinatorial optimisation, by searching over a large set of feasible solutions, metaheuristics can often find good solutions with less computational effort than optimisation algorithms, iterative methods, or simple heuristics (Blum and Roli, 2003). As such, they are useful approaches for optimisation problems. Heuristic methods tend to be ad hoc in nature; each method is usually designed to fit a specific problem type rather than a variety of applications (Hillier and Lieberman, 2010). A metaheuristic, in turn, is a general solution method that provides both a general structure and strategy guidelines for developing a specific heuristic method to fit a particular kind of problem.

A number of multi-objective metaheuristics can be found in the literature in papers such as Zambrano-Vega *et al.* (2017), Jones *et al.* (2002) and Bandyopadhyay *et al.* (2008). One of the most famous and popular multi-objective metaheuristics is NSGA-II, a multi-objective genetic algorithm. The Pareto archived evolution strategy (PAES) is another popular evolutionary multi-objective metaheuristic. There have been a number of proposals for multiple-objective simulated annealing (MOSA) algorithms, including: SMOSA, UMOSA, PSA, WMOSA and PDMOSA (Suman, 2004). The archived multi-objective simulated annealing (AMOSA) algorithm, developed by Bandyopadhyay *et al.* (2008), is another example. Tests run by Bandyopadhyay *et al.* (2008) show that the performance of their proposed AMOSA is better than that of MOSA and NSGA-II, in the majority of the cases tested, while PAES performs poorly, in general. AMOSA is found to provide more distinct solutions than NSGA-II in each run for all the problems tested, which is a desirable feature in MOO. AMOSA is less time-consuming than NSGA-II for complex problems like ZDT1, ZDT2 and ZDT6. Moreover, for problems with many objectives, the performance of AMOSA is found to be much better than that of NSGA-II. This is an interesting and most desirable feature of AMOSA (Bandyopadhyay *et al.*, 2008), since Pareto ranking-based multi-objective evolutionary algorithms (MOEAs), such as NSGA-II, do not work well on multi-objective optimisation problems, as pointed out in studies such as Hughes (2005) and Ishibuchi *et al.* (2006).

Table 4.4 Comparison of modelling tool performance in terms of desirable tool properties

Modelling Tool	Desirable Properties of the Tool								
	Prescriptive Model	Allow for Multiple Objectives	Compatible with Continuous Variables	Able to Adequately Explore an Infinite Search Space	Produce Solutions to Large Problems within a Reasonable Amount of Time	Level of Confidence in Results	Realistically Represent Reality and Relationships of Large, Complex Problems	Preserve Dimensionality and Dependencies Between Decision Variables	Accommodate Non-Differentiable Objective Functions
Traditional Optimisation	✓	×	✓	×	✓	Absolute	×	×	✓
Metaheuristics	✓	✓	✓	✓	✓	High	×	×	✓
Traditional Simulation	×	✓	✓	×	×	High	✓	✓	×
Enumeration	×	✓	×	×	×	Absolute	×	×	×
Multi-Objective Optimisation	✓	✓	✓	×	✓	Absolute	×	×	✓
Discrete Simulation Optimisation	✓	✓	×	×	✓	High	✓	✓	×
Gradient-Based Simulation Optimisation	✓	✓	✓	✓	✓	High	✓	✓	×
Metaheuristic Simulation Optimisation	✓	✓	✓	✓	✓	High	✓	✓	✓

Furthermore, it may be noted that in single objective evolutionary algorithms, or simulated annealing, a worse solution usually has a non-zero chance of surviving in subsequent generations, because this leads to a reduced possibility of getting stuck in sub-optimal regions (Bandyopadhyay *et al.*, 2008). In AMOSA, as in other versions of multi-objective SA algorithms, there is also a possibility that a new solution worse than the current solution may be selected. This makes the AMOSA algorithm less greedy in nature; thereby leading to better performance for complex or deceptive problems in most MOEAs (e.g., NSGA-II and PAES). However, if a choice needs to be made between two solutions x and y, and if x dominates y, then x is always selected (Bandyopadhyay *et al.*, 2008).

Based on the AMOSA algorithms' ability to deal with complex and deceptive problems, given the fact that the size and shape of the solution for the problem at hand is completely unknown and the algorithms' proficiency in dealing with multi-objective optimisation problems, the AMOSA algorithm was selected as the MOO metaheuristic of choice for the case study tool development.

4.4 Introduction to the AMOSA Algorithm

AMOSA (Archived Multi-Objective Simulated Annealing) is a simulated annealing based multi-objective optimisation algorithm that incorporates the concept of an archive in order to provide a set of trade-off solutions for the problem under consideration. To determine the acceptance probability of a new solution vis-a-vis the current solution, an elaborate procedure is followed that takes into account the domination status of the new solution over the current solution, as well as over those in the archive. A measure of the amount of domination between two solutions is used for this purpose (Bandyopadhyay *et al.*, 2008).

To better explain the algorithm, a general understanding of the simulated annealing metaheuristic is needed. Simulated annealing (Kirkpatrick *et al.*, 1983) is a probabilistic technique for approximating the global optimum of a given function. Specifically, it is a metaheuristic to approximate global optimisation in a large search space. The name and inspiration come from annealing in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects. Both are attributes of the material that depend on its thermodynamic free energy, which is affected by heating and cooling of the material. The notion of slow cooling implemented in the SA algorithm is interpreted as a slow decrease in the probability of accepting worse solutions, as the solution space is explored. Accepting worse solutions is a fundamental property of metaheuristics, because it allows for a more extensive search for the global optimal solution.

In general, the simulated annealing algorithm works as follows. At each time step, the algorithm randomly selects or generates a solution close to the current one, measures its quality and then decides to move to it or to stay with the current solution, based on a decision criterion which determines whether the new solution is better or worse than the current one. At each step, the probability of moving to a better solution is equal to one, however, the probability of moving to a worse new solution progressively changes towards zero. This progressive change is governed by a cooling schedule and the probability of acceptance of a worse solution is directly related to the temperature at the time. The algorithm accepts bad solutions in an attempt to avoid getting trapped in local optima.

Initially, the temperature is set high and, correspondingly, the chance of accepting a bad solution is high. This gives the algorithm a lot of freedom to explore the search space. As time progresses, the temperature is cooled down and it becomes less likely that the algorithm will move to points that are not improving on the fitness function. This forces the algorithm to explore the local region in more detail. Re-annealing is a technique that can be used to avoid getting trapped in a local optimum, by performing the whole SA algorithm up to the point where a local optimum is found and then resetting the temperature to the maximum level - essentially running the entire SA again, but from a different starting point.

Figure 4.8 provides the pseudocode for the standard SA algorithm, as documented by Suman and Kumar (2006). In 1984, Geman and Geman provided proof that SA, when annealed sufficiently slowly, converges to the global optimum (Geman and Geman, 1984).

1. Initialize the temperature.
2. Start with a randomly generated initial solution vector, X, and generate the objective function.
3. Give a random perturbation and generate a new solution vector, Y, in the neighbourhood of current solution vector, X, revaluate the objective function and apply penalty function approach to the objective function, if necessary.
4. If the generated solution vector is archived, make it the current solution vector by putting $X = Y$. Update the existing optimal solution and go to Step 6.
5. Else accept Y with the probability:

   $$P = \exp(-\Delta s/T) \qquad (1)$$

   where $\Delta s = Z(Y) - Z(X)$.
   If the solution is accepted, replace X with Y.
6. Decrease the temperature periodically.
7. Repeat Steps 2–6 until stopping criterion is met.

Figure 4.8 Single objective simulated annealing pseudocode (Suman and Kumar, 2006)

In contrast to most other MOO algorithms, AMOSA selects dominated solutions with a probability that is dependent on the amount of domination measured in terms of the hypervolume between the two solutions in the objective space. Given two solutions *a* and *b*, the amount of domination is defined as

$$\Delta dom_{a,b} = \prod_{i=1, f_i(a) \neq f_i(b)}^{M} \frac{|f_i(a) - f_i(b)|}{R_i},$$

where *M* equals the number of objectives and R_i is the range of the i^{th} objective (Bandyopadhyay *et al.*, 2008). Note that in several cases, R_i may not be known a priori. In these situations, the solutions present in the archive, along with the new and the current solutions, are used for computing it. The concept of $\Delta dom_{a,b}$ is illustrated pictorially in Figure 4.9 for a two-objective case. $\Delta dom_{a,b}$ is used in AMOSA when computing the probability of acceptance of a newly generated solution.

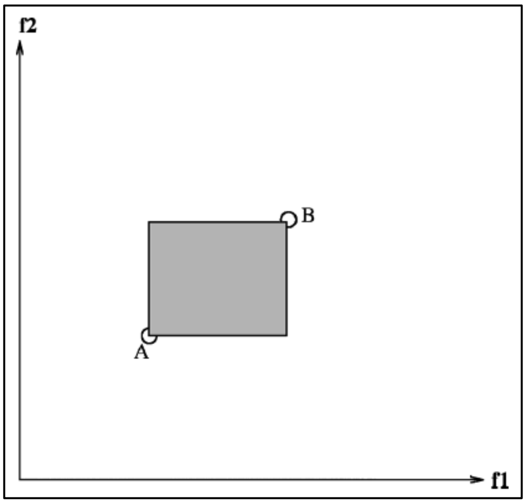


Figure 4.9 Illustration of the concept of $\Delta dom_{a,b}$ (Bandyopadhyay et al.*, 2008)*

The pseudocode for AMOSA is shown in Figure 4.10. The algorithm starts by randomly selecting a point in the archive as the initial solution at the maximum temperature. This is known as the current point. The current point is then perturbed in some way, generating a new solution (new point). The two points are then compared in terms of domination to determine how the archive will adapt. In AMOSA, one of three cases can arise based on the domination status between the current and the new point. In case one, the current point dominates the new point and zero or more points in the archive also dominate the new point. Figure 4.11 illustrates this case. In (a), none of the points in the archive dominate the new point, except for the current point, and in (b), there are points in the archive that also dominate the new point. In this case, the new point can be selected to replace the current point, based on a probability calculated as shown in the pseudocode.

Case two is where the current point and the new point are both non-dominating with respect to each other. The acceptance of the new point is then based on the domination status between the new point

Algorithm AMOSA

Set *Tmax*, *Tmin*, *HL*, *SL*, *iter*, α, temp=*Tmax*.
Initialize the *Archive*.
current-pt = random(*Archive*). /* randomly chosen solution from the *Archive* */
while (temp > *Tmin*)
  for (i=0; i< iter; i++)
    new-pt=perturb(*current-pt*).
    Check the domination status of *new-pt* and *current-pt*.
    /* Code for different cases */
    if (*current-pt* dominates *new-pt*) /* Case 1*/
      $\Delta dom_{avg} = \frac{\left(\sum_{i=1}^{k} \Delta dom_{i,new-pt}\right) + \Delta dom_{current-pt,new-pt}}{(k+1)}$.
      /* k=total-no-of points in the *Archive* which dominate *new-pt*, $k \geq 0$. */
      prob= $\frac{1}{1+exp(\Delta dom_{avg} * temp)}$.
      Set *new-pt* as *current-pt* with probability=*prob*
    if (*current-pt* and *new-pt* are non-dominating to each other) /* Case 2*/
      Check the domination status of *new-pt* and points in the *Archive*.
      if (*new-pt* is dominated by k ($k \geq 1$) points in the *Archive*) /* Case 2(a)*/
        prob= $\frac{1}{1+exp(\Delta dom_{avg} * temp)}$.
        $\Delta dom_{avg} = \frac{\left(\sum_{i=1}^{k} \Delta dom_{i,new-pt}\right)}{k}$.

        Set *new-pt* as *current-pt* with probability=*prob*.
      if (*new-pt* is non-dominating w.r.t all the points in the *Archive*) /* Case 2(b)*/
        Set *new-pt* as *current-pt* and add *new-pt* to the *Archive*.
        if *Archive-size* > *SL*
          Cluster *Archive* to *HL* number of clusters.
      if (*new-pt* dominates k, ($k \geq 1$) points of the *Archive*) /* Case 2(c)*/
        Set *new-pt* as *current-pt* and add it to the *Archive*.
        Remove all the k dominated points from the *Archive*.
    if (*new-pt* dominates *current-pt*) /* Case 3 */
      Check the domination status of *new-pt* and points in the *Archive*.
      if (*new-pt* is dominated by k ($k \geq 1$) points in the *Archive*) /* Case 3(a)*/
        Δdom_{min} = minimum of the difference of domination amounts between the *new-pt* and the k points
        prob= $\frac{1}{1+exp(-\Delta dom_{min})}$.
        Set point of the archive which corresponds to Δdom_{min} as *current-pt* with probability=*prob*
        else set *new-pt* as *current-pt*.
      if (*new-pt* is non-dominating with respect to the points in the *Archive*) /* Case 3(b) */
        Set *new-pt* as the *current-pt* and add it to the *Archive*.
        if *current-pt* is in the *Archive*, remove it from the *Archive*.
        else if *Archive-size*> *SL*.
          Cluster *Archive* to *HL* number of clusters.
      if (*new-pt* dominates k other points in the *Archive*) /* Case 3(c)*/
        Set *new-pt* as *current-pt* and add it to the *Archive*.
        Remove all the k dominated points from the *Archive*.
  End for
temp= $\alpha *$temp.
End while
if *Archive-size* > *SL*
  Cluster *Archive* to *HL* **number of clusters.**

Figure 4.10 Pseudocode for the AMOSA algorithm (Bandyopadhyay et al.*, 2008)*

and members of the archive, with three possible outcomes (see Figure 4.12). First, the new point can be dominated by a number of points in the archive (Figure 4.12(a)). In this case, there is a certain probability that the new point will replace the current point. Second, the new point is non-dominating with respect to all the members of the archive (Figure 4.12(b)) and will be selected as the current point and added to the archive. Thirdly, the new point dominates some points in the archive (Figure 4.12(c))

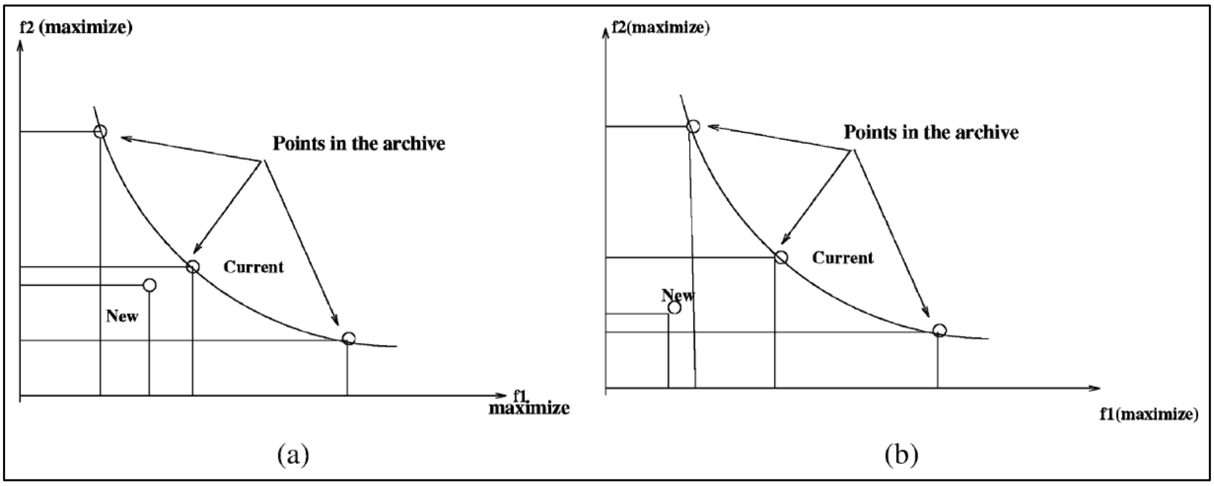


Figure 4.11 AMOSA case 1: the new point is dominated by the current point and points in the archive (Bandyopadhyay et al.*, 2008)*

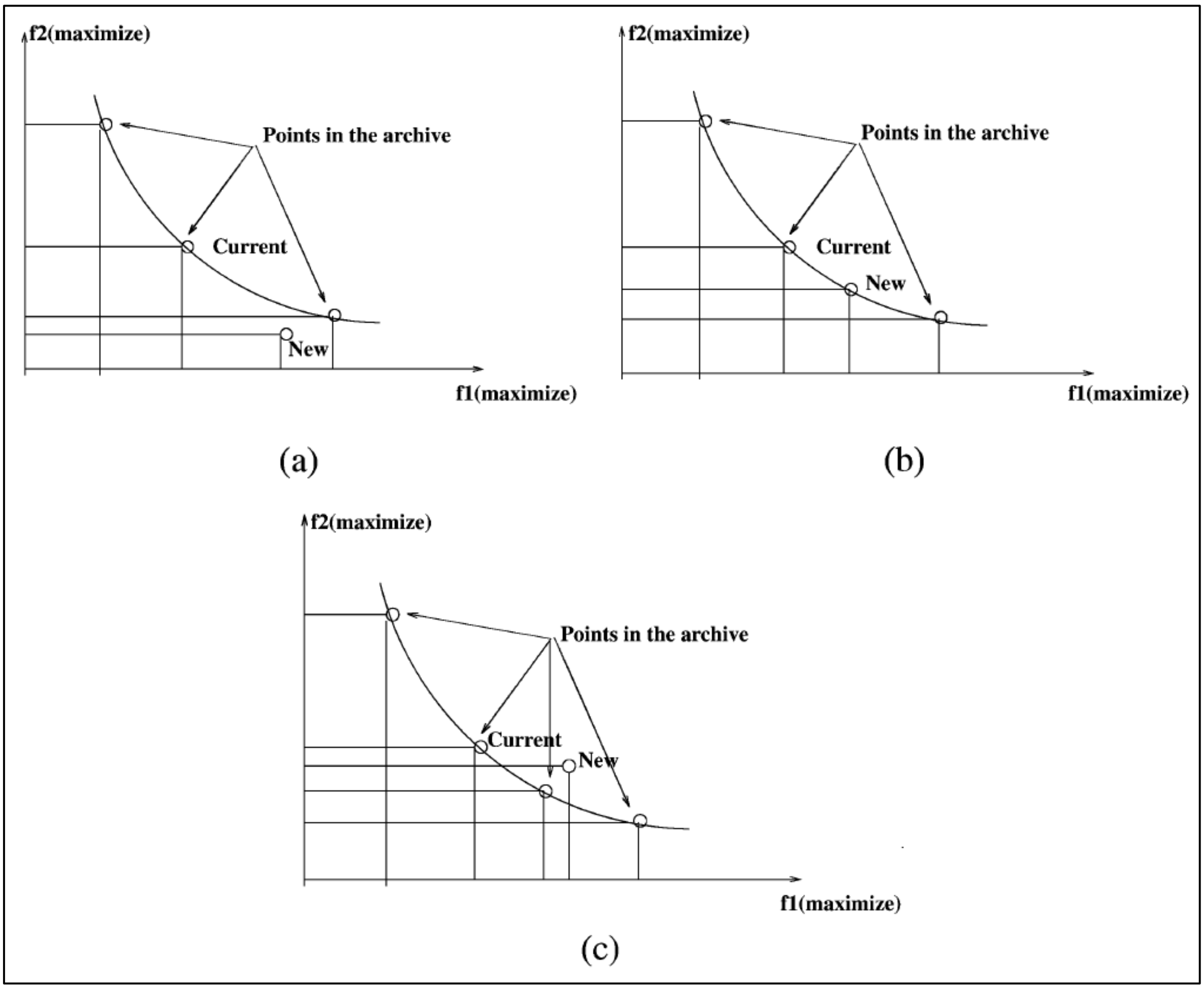


Figure 4.12 AMOSA case 2: the new point and current point are both non-dominating on each other (Bandyopadhyay et al.*, 2008)*

and, again, will be set as the current point and added to the archive. All dominated points are removed from the archive.

In case three, the new point dominates the current point and, based on the domination between the new point and the archive, one of three situations can arise (Figure 4.13). In the first of these situations there are points in the archive that dominate the new point (Figure 4.13(a)). The point in the archive with the lowest domination over the new point is selected as the current point with a certain probability. Failing that, the new point becomes the current point. The second situation is when the new point is non-dominating with respect to all the members of the archive (the current point excluded). This is depicted in Figure 4.13(b). The new point is added as a new non-dominated point to the archive and the current point removed from the archive, if it was a member. In the third situation (Figure 4.13(c)), the new point also dominates a number of points in the archive. Here, the new point is selected as the current point, added to the archive and the dominated points in the archive are removed from the archive.

Once the comparison between the new and current point has been completed and the current point and archive have been updated, the process is repeated for a number of iterations (as specified by the modeller), before the temperature is decreased (and the probability of accepting a proposed solution is reduced). The process repeats itself at every new temperature and the temperature declines with a cooling rate specified by the modeller, until the minimum temperature is reached. This signals the end of the process and the archive (at this point in time) contains the final set of non-dominated solutions to the problem (the Pareto set). For more detailed insight into the AMOSA algorithm, the reader is referred to Bandyopadhyay *et al.* (2008).

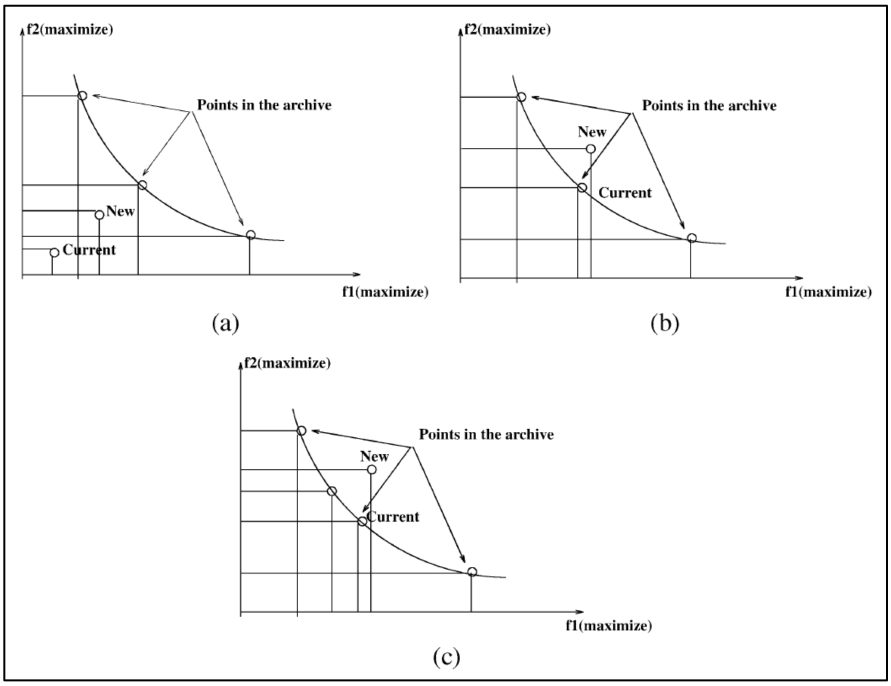


Figure 4.13 AMOSA case 3: the new point dominates the current point (Bandyopadhyay et al.*, 2008)*

4.5 Chapter Summary

In this chapter, a detailed analysis of the problem formulation revealed a requirement specification for the modelling tool to be used to address the problem. Following the definition of the specification, a short summary of several popular decision support tools was provided. The characteristics of each tool was paired with the tool requirements and simulation optimisation was identified as the decision support tool of choice. The chapter then provided a more detailed description of simulation optimisation and the multiple-objective optimisation algorithms suitable for use in this case. An explanation on the reasoning behind the selection of the AMOSA algorithm for use in the case study model was given next, followed by a description of AMOSA.

The chapter addressed research question 2.16 (which decision support modelling tool is the most appropriate) and partially answers question 3.1 (is the simulation optimisation modelling methodology appropriate) by confirming the choice of simulation optimisation, in theory.

5 Solution Procedure Development

With the modelling tool to be used determined (as discussed in Chapter 4), the next (fourth) step in the standardised operations research process is to develop the solution procedure. This refers to the actual computer programming to create the decision support tool required. All the information gathered and decisions made in the previous steps and chapters are now combined, culminating in a physical, computerised solution procedure that will be used to generate solutions to the problem in question. This chapter explains the logic followed in development of the Freight Transport Energy Management Tool (FTEMT) proposed in this dissertation.

The FTEMT is a simulation optimisation model, implying that the model is primarily an optimisation algorithm aimed at identifying the optimal set of input parameters to a simulation model. The simulation model is a stand-alone procedure which is repeatedly run by the optimisation algorithm, forming only one step in the FTEMT's search process. Figure 5.1 shows the logic structure of the FTEMT. Procedures and decisions coloured blue form part of the optimisation algorithm and the purple procedure represents the simulation model. The optimisation components determine what changes are to be made to the decision variable combinations in each explored solution and whether an acceptable number of combinations have been explored, while the simulation model is used to determine the impact of each combination in terms of the objectives, thereby assessing the quality of each explored solution. Put differently, the optimisation algorithm defines the inputs to a particular instance of the simulation model. The simulation model then transforms these inputs into impacts that are measured over the assessment criteria, forming the simulation model outputs which are used by the optimisation model to determine what other decision variable combinations to explore next. This interaction, where the optimisation model invokes several instances of the simulation model, is summarised and explained in Figure 1.7 in Section 1.5 and in Section 4.3.

Both the optimisation and simulation model components of the FTEMT are discussed in detail in this chapter in Sections 5.1 and 5.2, respectively. This is followed by a description of how the model addresses the problem complexities (highlighted in Section 1.2) in Section 5.3. Section 5.4 describes verification of the solution procedure.

5.1 The Optimisation Procedure

The flow chart elements coloured blue in Figure 5.1 Flow chart of the FTEMT logic correspond to decisions and processes from the AMOSA algorithm (discussed in Section 4.4). The FTEMT starts by loading the a priori parameter values that determine the annealing schedule to be used in the AMOSA algorithm for this particular instance of the FTEMT. These values are termed a priori because they need not be determined during the application of the FTEMT; they can be set by the modeller based on previous knowledge or experience. Following this step, an initial archive of solutions is generated by running multiple versions of the simulation model. A solution is the set of values associated with each decision made in the simulation model, as explained in Section 4.1. This set of decision values corresponds with a particular set of outcomes in terms of the problem objectives. In other words, it is the specific combination of input parameters to the simulation model that yields a specific set of outputs. It is important to note that, if the simulation model is rerun with exactly the same input parameters and decisions made, it will yield exactly the same output.

In the next step, one solution from the initial archive is randomly selected. This chosen solution is dubbed the *current* solution. A randomised selection procedure then determines which decision variable serving as input to the simulation model (there are 14 such decision variables in the case study model presented in this dissertation) will be changed in this iteration of the optimisation algorithm. The simulation model is run next, utilising the decision variable values corresponding to those in the *current* solution, in combination with a random change to the decision variable selected in the previous step. The dependencies between decision variables, as well as their dimensionality, has been discussed in Section 4.1. Should the randomly selected decision variable have other decision variables dependent on it, the value of all decisions relating to that variable and all its dependents will be newly determined over all dimensions within the simulation model. All independent decision variables and the decision variables on which the chosen one is dependent will remain exactly the same over all dimensions as in the *current* solution. This means that the new solution generated when running the simulation model is not completely random, nor completely independent of the *current* solution. It is rather a mutation of the *current* solution. In terms of optimisation theory this represents exploration of the search space by taking steps in the vicinity of the *current* solution.

The output from this simulation run is dubbed the *new* solution and the domination status between the *new* and the *current* solution is determined. The domination status of the *new* solution and the archive is then calculated and, based on the rules set out in the AMOSA algorithm, the *current* solution is, potentially, replaced and the archive updated. If the rules determine that the *current* solution should be replaced by the *new* solution, a solution replacement counter is updated. This counter is used as a stop criterion for searching the solution space at the current temperature. If this stop criterion is satisfied, i.e. the maximum number of exploitation steps have been taken at the current temperature, the cooling schedule is applied and the solution replacement counter is reset. Unless all

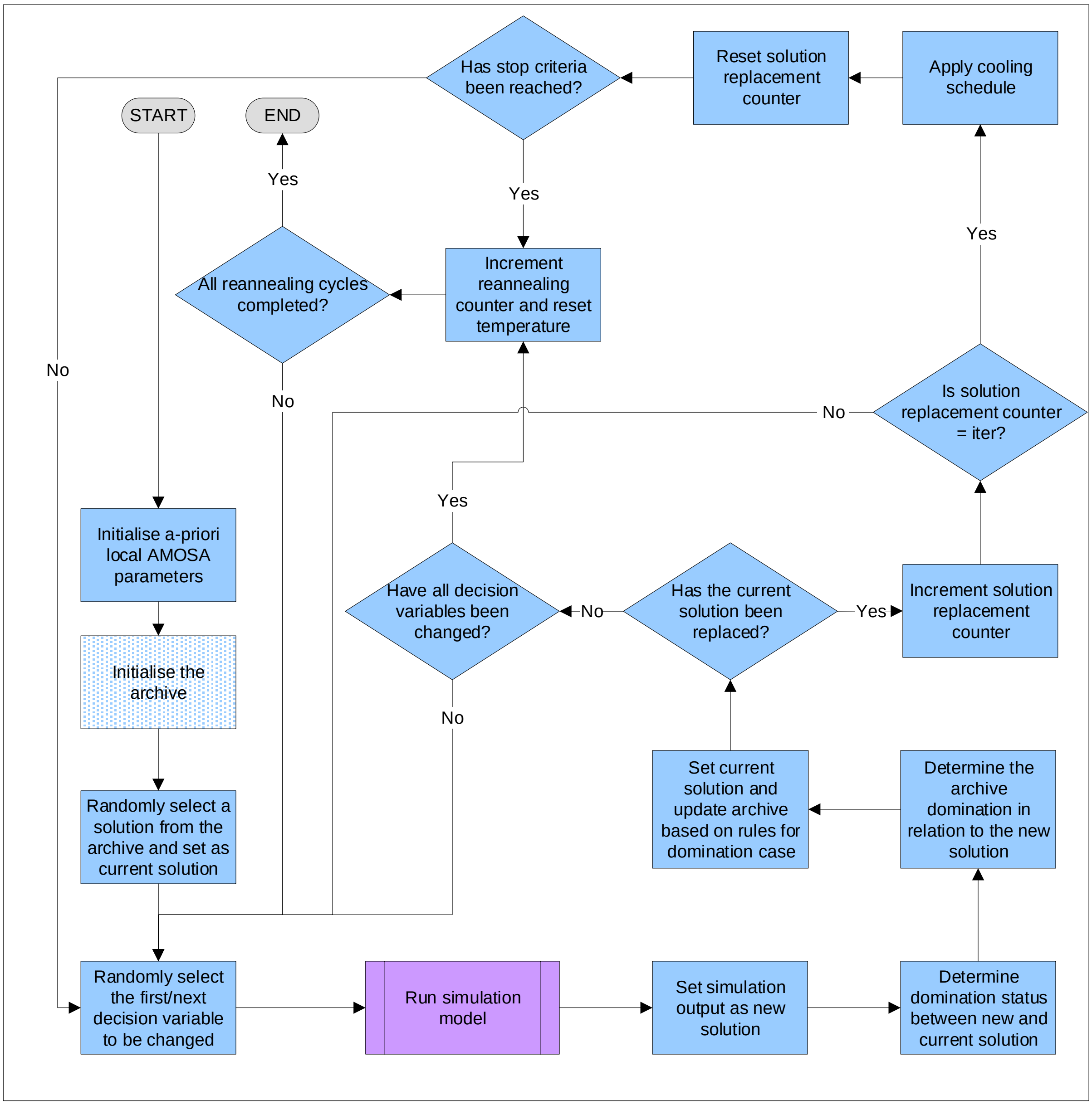


Figure 5.1 Flow chart of the FTEMT logic

exploration has been completed at the minimum temperature, a new decision variable to be modified is randomly selected before the simulation model is run again and the whole process repeats itself.

Reannealing is the term used in simulated annealing where the temperature is raised after the algorithm has accepted a certain number of new points and the cooling schedule has been completed (MathWorks, 2019). With reannealing the search continues from the reset higher temperature and the entire cooling schedule is repeated. Though it is not a required part of a simulated annealing algorithm, it is generally done in an attempt to avoid the algorithm getting caught in local optima by enabling greater exploration within the search. There is a higher probability of accepting inferior solutions at higher temperatures, enabling the algorithm to move away from a locally optimal solution. The search and sampling of solutions around the current solution at the same temperature (i.e. with the same probability of acceptance) serves to facilitate exploitation of the solutions already in the archive. The number of iterations at a specific temperature directly correlates with the level of exploitation achieved. It is the goal of any metaheuristic modeller to strike a good balance between exploration of the search space (where the search algorithm has the freedom to take large steps and explore solutions far away from the incumbent solution) and exploitation of good solutions found to date (where search steps are smaller and more structured, to ensure that the search space in the vicinity of an already good solution is thoroughly explored). A thorough explanation of the exploration-exploitation trade-off in metaheuristics is provided by Junqin and Jihui (2014).

The FTEMT has been developed with a reannealing option. Once the cooling schedule is completed, the algorithm checks whether all reannealing cycles have been completed. If reannealing should still take place, the temperature is reset to the maximum value, a new decision variable is chosen to manipulate and the process continues. When all reannealing cycles have been completed, the optimisation algorithm comes to an end and the archive, at this point in time, represents the Pareto set of solutions to the problem (or as near an estimate of the Pareto set as can be determined by the model).

Alternatively, if the AMOSA algorithm's rules for domination determines that the *current* solution should not be replaced by the *new* solution, a different decision variable to the one changed to form the *new* solution is randomly selected from the remaining decision variables that have not yet been changed at this temperature and the process continues. An additional stop criterion is activated if all the decision variables have already been selected and modified prior to this point at the current temperature and the required number of improving steps have not yet been taken. This means that no tweak to any decision variable in the *current* solution at the current temperature could generate an accepted *new* solution and the model is stuck at a local optimum. The algorithm then terminates the search at this temperature (eliminating any further exploitation of this solution) and a reannealing cycle is started, should all reannealing cycles not yet be completed.

5.1.1 Determination of the a priori local parameters

The domination-based decisions on whether to replace or keep the *current* solution in AMOSA is another lever (apart from the number of iterations at a set temperature) with which the levels of exploration and exploitation can be adjusted in the algorithm. The predilection and sensitivity of these decisions on the exploration-exploitation trade-off, in turn, are dependent on the a priori parameter settings. It is good modelling practice to identify the best a priori parameter settings for the model at hand when the model is being developed. This is typically achieved by incremental variation of the parameter values and inspection of the resultant impact on the model outputs. This impact is assessed in terms of the quality of the solutions produced, as well as the model run time. A greater number of steps does improve the solution quality, but takes longer to achieve it. Here, too, there is a trade-off that the modeller must balance. Configuration and determination of the ideal parameter settings is a time-consuming process, but need only happen once, initially for each new application of the FTEMT. The same settings can then be used for subsequent model applications, should the fundamental model structure not change.

Suman and Kumar (2006) provide an overview of how an annealing schedule should be determined in a simulated annealing algorithm. There are four main components of an annealing schedule: the initial temperature (T_{max}), the cooling schedule (α), the number of iterations to be performed at each temperature (*iter*) and the stop criterion used to terminate the algorithm.

The initial temperature should ideally be so chosen that it allows the algorithm to perform a random walk over the entire solution space, i.e. it should start high enough to allow thorough exploration. The cooling schedule determines the functional form of the change in temperature. In terms of setting the cooling rate, a high cooling rate can lead to poor results, because of a potential lack of representative states, while a low cooling rate requires high computation time to get the result (Suman and Kumar, 2006). The most frequently used decrement rule, also used in this dissertation, is the geometric schedule given by $T_{k+1} = \alpha T_k$, where $\alpha \in (0,1)$ and α denotes the cooling factor. Typically, the value of α is chosen in the range between 0.5 and 0.99. This cooling schedule has the advantage of being very simple. Some other cooling schedules available in the literature are logarithmic, Cauchy and exponential schedules.

The third component of an annealing schedule is the number of iterations performed at each temperature. As suggested by Suman and Kumar (2006), the value of the number of iterations should be chosen depending on the nature of the problem. This value is also utilised in AMOSA. The FTEMT, however, varies from the AMOSA algorithm in this regard. In the FTEMT, the number of iterations per temperature is not fixed, but there is a fixed number of successful steps to be taken by the model (denoted as the solution replacement counter in Figure 5.1), with a fixed number of attempts at finding a successful step allowed (14 in the case study model). This is done to accommodate the large range of ways in which the *current* solution can be modified to generate the *new* solution. As mentioned, if a change to a particular decision variable is unsuccessful, the FTEMT will attempt to change a different decision variable in the next iteration. This enables greater exploitation of the *current* solution, by cycling through all options for generating a *new* solution (14 in the case study model). It is possible to add an additional layer in the FTEMT where there is a fixed number of attempts to change a specific decision variable before the algorithm discards the variable as non-viable for generating acceptable *new* solutions. This would further improve exploitation of the current solution, as it allows exploitation of the changes allowable to the decision variable as well. It is worth considering when, as in the case study model, the range of ways in which a decision variable can be changed, is extensive. It will, however, have a marked impact on model run time and for this reason it was excluded from the case study model.

Several criteria have been developed for termination of a simulated annealing process. In some of them, the total number of iterations that the algorithm must execute is given, whereas in some others, the minimum value of the temperature is specified. A detailed discussion on this issue can be found in Suman and Kumar (2006). The AMOSA algorithm (and, therefore, the FTEMT) uses a minimum temperature (T_{min}) to end the search.

When selecting T_{max} and T_{min}, the effect that these values will have on the acceptance probability of a non-dominant solution needs to be borne in mind, as temperature forms part of the equation to calculate this probability. Depending on the problem being modelled, there could be a scaling issue if the temperature value is not in the same order of magnitude as the domination amount used in the same equation.

Another deviation of the FTEMT from AMOSA pertains to the size of the archive used. In AMOSA, the size of the archive is restricted and two additional a-priori parameters (*HL* and *SL*) are used. These parameters are used to set the maximum archive size and a level at which clustering of solutions in the archive should occur, should the maximum size be exceeded. The FTEMT model keeps all solutions in the archive to create as dense possible Pareto set of solutions. No clustering is applied; hence, these parameters are excluded from the FTEMT. An additional a priori parameter used in the FTEMT is a setting for the number of reannealing cycles to be run. If the modeller wishes to run the tool without reannealing, this parameter is set to one.

The similarities and differences between then AMOSA algorithm and the algorithm used in FTEMT is summarised in the comparison table presented in Table 5.1.

There are no uniform guidelines for choosing the a priori parameters in a simulated annealing-based algorithm (Suman and Kumar, 2006). Empirical performance evaluation of multi-objective metaheuristics mainly involves assessing the quality of solutions found and the computational resources required to generate these solutions (Talbi, 2009). The final parameter configuration used

Table 5.1 Comparison between the configuration of the AMOSA and FTEMT algorithms

A Priori Parameter	AMOSA	FTEMT
Number of iterations per temperature setting	Fixed number of iterations	Fixed number of successful steps taken, and fixed number of attempts allowed to find a successful step
Termination criterion	Minimum temperature	Minimum temperature
Limitations on the size of the archive	Restricted through clustering to contain size	Unrestricted, all solutions are kept
Reannealing	Not included	Included

in the case study application of the FTEMT was decided upon through testing eight different combinations of the a priori parameters and their respective impacts on computational effort and solution quality. All eight versions departed from the same initial archive. The different parameter settings per combination are shown in Table 5.2.

Table 5.2 A priori parameter settings of eight variants compared during the case study model development

Parameter	A Priori Parameter Combination							
	1	2	3	4	5	6	7	8
T_{max}	3	3	3	3	6	3	3	3
T_{min}	0.5	0.5	0.5	0.5	0.25	0.5	0.5	0.5
α	0.5	0.5	0.5	0.5	0.5	0.2	0.8	0.5
iter	3	3	6	3	3	3	3	3
Reannealing cycles	3	3	3	6	3	3	3	3
Reanneal from new current solution	No	No	No	No	No	No	No	Yes
Algorithm repetitions	1	2	1	1	1	1	1	1

The first combination was the default combination on which all other modifications were based. In combination two the entire AMOSA algorithm ran twice, doubling the run time of the model, but keeping the balance between exploration and exploitation the same. The third combination doubled the number of successful steps required per temperature level. In combination four, there were twice as many reannealing cycles as in combination one. The fifth combination, in turn, experimented with a change to the temperature range used in the model (both T_{max} and T_{min} were changed to increase this range), whilst the cooling schedule was modified in combinations six (faster cooling) and seven (slower cooling). Combination eight looked at the impact of starting a reannealing cycle with a newly selected archive solution set as the *current* solution, as opposed to continuing with the *current* solution as determined by the algorithm at that point in time.

A comparison of the performance of each combination in terms of several performance measurement metrics is provided in Table 5.3. Colour coding is used to show the preferred combination over each metric, where the darkest green value represents the best performance and the darkest red the worst performance in each row.

The computation time performance metric is often reported in terms of CPU time or wall clock time, but a key drawback of using this assessment metric is that is depends on the computer characteristics used to run the model, such as the hardware (e.g. the processor, memory and specification parallel architecture), the operating system, the coding language and the compiler (Talbi, 2009). Indicators independent of the computer system, such as the number of objective function evaluations, can also be used in time-insensitive and constant objective functions (Talbi, 2009). The number of solutions explored in each parameter configuration are shown in Table 5.3.

Table 5.3 Performance assessment and comparison between AMOSA algorithms with different a-priori parameter settings

Performance Metric	A Priori Parameter Combination							
	1	2	3	4	5	6	7	8
Number of solutions explored	40	77	72	67	69	18	124	34
Size of the Pareto front	28	35	33	37	32	22	53	17
Overall non-dominated solution generation ratio	33%	41%	38%	43%	37%	26%	62%	20%
Purity	68%	86%	52%	68%	91%	64%	51%	65%
Generational distance	0.0749	0.0885	0.1778	0.1104	0.0697	0.1329	0.1154	0.4715
Spacing	3.3011	2.894	3.4558	3.4641	4.0541	3.855	3.3887	4.8537

When the cooling rate is slowed down (parameter combination seven), the greatest number of solutions are explored and the largest Pareto front is created. Van Veldhuizen and Lamont (2000) state that, although counting the number of non-dominated solutions gives a feeling for how effective an algorithm is in generating desired solutions, it fails to reflect on how close the solutions are to the true Pareto set. As it is difficult to determine what good levels of this metric would be, they suggest rather reporting on the ratio of the cardinality of solutions in the generated Pareto front to the cardinality of solutions in the true Pareto front. This gives some feeling for the number of non-dominated solutions found versus how many exist to be found. The true Pareto front is, however, unknown, as is the case with most real-life problems (Talbi, 2009). In this case, performance is evaluated in terms of a reference set, enabling a relative performance comparison. The reference set was created by combining all the non-dominated solutions found over all eight parameter combinations and by removing duplicates and solutions that may not be non-dominant over this new set. Essentially, it is the set of non-dominated solutions that remain when all the solutions generated are combined. This reference set is used as a proxy for the true Pareto set (it is, however, impossible to determine how close this set is to the actual Pareto set).

The overall non-dominated solution generation ratio (*ONVGR*) is defined by van Veldhuizen and Lamont (2000) as

$$ONVGR \triangleq \frac{|PF_{known}|}{|PF_{reference}|}$$

where

PF_{known} = the number of non-dominated solutions in the Pareto front generated with the parameter combination in question, and

$PF_{reference}$ = the number of non-dominated solutions in the reference Pareto front.

A ratio of one would indicate that the algorithm in question has found the same number of solutions as in the reference front. Higher values of this ratio are, thus, preferred over lower values.

Purity is a metric used to compare solutions by calculating the fraction of solutions from a particular algorithm that remains non-dominating when the reference front of solutions, obtained from all algorithms to be compared, are combined (Bandyopadhyay *et al.*, 2008). A value close to 100% indicates better performance and close to 0% poorer performance.

The quality of a solution needs to be assessed in terms of both convergence to the true Pareto front and diversity of solutions along the front (Talbi, 2009). Generational distance is one indicator of convergence that does not require the true front to be monotone (the shape of the true Pareto front is unknown in this real-world application) and can make use of a reference set, as opposed to the true Pareto set (Talbi, 2009), making it a viable option to use in this dissertation. The generational distance (*G*) computes the average distance between the approximated set and a reference set. Van Veldhuizen and Lamont (2000) define it as

$$G \triangleq \frac{\left(\sum_{i=1}^{n} {d_i}^p\right)^{1/p}}{n}$$

where

n = the number of solutions in PF_{known},

p = the number of objective dimensions, and

d_i = the Euclidean distance in the objective space between each solution and the nearest member of $PF_{reference}$.

A generational distance of zero would indicate that the approximated front is equal to the reference front.

Spacing is an indicator of diversity (Bandyopadhyay *et al.*, 2008; Talbi, 2009). Its value measures the spread (distribution) of solutions throughout PF_{known} (van Veldhuizen and Lamont, 2000). The spacing metric (S) is calculated by

$$S \triangleq \sqrt{\frac{1}{n-1}\sum_{i+1}^{n}(\bar{d}-d_i)^2}$$

where

d_i = the Euclidean distance between adjacent solutions in PF_{known}, $i \in [1, \dots, n]$,

$\bar{d}$ = the mean of all d_i, and

n = the number of solutions in PF_{known}.

Smaller values of spacing indicate better performance (Bandyopadhyay *et al.*, 2008).

Although these performance metrics cannot guarantee actual performance of the algorithms, especially given the limitations of being able to prove this in terms of the true Pareto front, they do provide a relative sense of performance and are, thus, considered useful in terms of comparing the various parameter settings.

Table 5.3 shows that parameter combinations seven, four and two, respectively, are the best performers over the ONVGR metric, with combination seven being substantially better. Combination five, followed by combination two, are the best performers in terms of purity, in turn. Similarly, it is shown that combinations five, one and two (respectively) appear to be the best performers in terms of convergence and that combination two outperforms the other combinations in terms of diversity.

Combination seven is the best performer in terms of computational efficiency, although it has the longest runtime of all the combinations. Combination two, however, is the best performer in terms of solution quality. This combination also performs well in terms of computational efficiency and is, overall, the most balanced algorithm achieving good performance over all metrics. The second-best solution, in terms of quality, is produced by combination one. This combination has almost half the runtime of combination two, but this comes at a cost of exploring almost half the search space that combination two explores. Doubling the number of searches per temperature (combination three) does add some value in terms of exploitation and computational efficiency, but the solution quality is inferior to the base combination. Doubling the reannealing cycles (combination four), in turn, does provide a good balance between computational effort, exploration and solution quality, although it is outperformed by simply repeating the basic search algorithm (combination two). A larger temperature range (combination five) yielded a marked increase in exploitation, exploration and computational efficiency, coupled with a very good solution in terms of purity and convergence. The diversity of the solution was, however, not on par with that of the other combinations, negatively impacting on the overall solution quality. Speeding up the cooling schedule (combination six) performed poorly on all assessment metrics and is not advised. Despite the increased exploitation and search capabilities resulting from a decrease in the cooling schedule (combination seven), the quality of the solutions found was not on par with the other combinations, making this time-expensive combination not worth the additional resources it requires. Finally, combination eight, where there is a lot less exploitation and a greater emphasis on exploration, is the worst performer.

Depending on the computational resources and time available, combinations two (longer runtime) and four (faster) strike the best balance between exploration and exploitation. Application of the FTEMT will, typically, not have to occur dynamically, nor too frequently, so that the longer runtime is a once-off penalty that does not supersede the gain in solution quality of applying combination two. The a priori parameter settings in combination two were chosen as the preferred combination for use in the case study model and all results from the case study application are related to the outputs from this model configuration.

5.1.2 Initialising the archive

The algorithm begins with the initialisation of a fixed number of solutions. The number of solutions in the initial archive are determined by the modeller and there are no set guidelines regarding the size of the initial archive, although a larger archive implies longer runtime juxtaposed with greater exploration. In the case study model, the initial archive size was set to 30 solutions. A solution is generated by running an instance of the simulation model with completely random values for all the decision variables. This is repeated 30 times, each time with new decision variable values and the outputs (along with the corresponding input values) of each run are stored in the archive.

Once the archive is populated with the required amount of random solutions, a domination check is performed to identify and eliminate any dominated solutions. This potentially reduces the size of the initial archive. If the resultant initial archive is deemed too small by the modeller, additional random solutions can be generated, checked for domination and, if non-dominant, added to the archive. This process can be repeated until the preferred size of the archive has been populated by only non-dominated solutions. It is, however, acceptable to have an initial archive of size one (Bandyopadhyay *et al.*, 2008). The case study model was set to use the surviving number of non-dominated solutions after the domination check had been completed, even if this reduced the initial archive size below 30 solutions. The resultant initial archive now contained 13 solutions.

The AMOSA algorithm specifies that each solution in the initial archive be refined by applying a simple hill-climbing technique, accepting a new solution only if it dominates the starting solution (Bandyopadhyay *et al.*, 2008). Hill-climbing is a form of local search where the search starts at a given initial solution and, at each iteration, the heuristic replaces the *current* solution by a neighbour that improves the objective function, until the stop criterion is reached or no more improving steps can be taken (Talbi, 2009). Refining the initial archive is not strictly necessary. An improved archive could potentially advance the algorithm's ability to find a better solution, but quantifying how much of a benefit this would be is not possible. Running a hill-climbing search adds to the computational runtime of generating the initial archive.

The hill-climbing algorithm applied in the case study model randomly changed the value of each of the decision variables one by one to explore the area around every archive solution. The space around each archive solution was, thus, sampled 14 times. If the sampled solution dominated the solution in the archive, the archive solution would be replaced by the dominant solution and all subsequent searches compared to this updated solution. A total of 182 (13 archive solutions x 14 steps) solutions were explored and no improvements to the initial archive were found. This is because an accepted solution had to be strictly better than the initial solution; non-dominated (equally good) solutions were not accepted or added to the archive. It would be acceptable to eliminate the hill-climbing search in future applications of the case study model.

5.1.3 Feasibility testing

Feasibility testing is standard practice in metaheuristics where random solutions are generated. The feasibility test is performed to ensure that solutions still comply with the problem constraints (both implicit and explicit). As the random values generated in the FTEMT are generated to fall within the variable boundaries defined in Section 3.2.15, all solutions will be inherently feasible and an additional feasibility test is not required.

5.2 The Simulation Procedure

For a simulation model to achieve its design goal, it is important to have a good understanding of what the model needs to deliver for it to be deemed a success (Kelton *et al.*, 2004). The simulation model developed in the FTEMT should capture the complex interactions between the various elements of the freight transportation system and should measure system-wide impacts of changes to the system.

The end goal of this simulation model is to assign freight demand in the network (i.e. to decide how the freight will be transported between origins and destinations) subject to the system boundaries defined by the decision variable input values. These input values are determined in the optimisation model and shape the freight assignment decisions that can be made in the transformation phase of the simulation model. The impact of each particular network assignment is calculated and these impact values form the model output, which is used by the optimisation model to inform on what changes to make to the input variables of subsequent runs of the simulation model. The simulation model does not have to assess the quality of the output and no value assessment is done when making assignment decisions in the simulation model. The FTEMT's simulation model can be classified as a static, discrete and deterministic model.

5.2.1 Input phase

The input phase of the simulation model is used to gather and prepare the parameters to be used in the transformation phase. There are two types of parameters used in the model: global parameters and local parameters. Global parameters are parameters that never change (neither during, nor between simulation runs) and can be described as fixed system characteristics. Local parameters, in turn, are determined for the specific simulation run in question. The decision variable values serve as local parameters in this model, whilst the global parameters reflect the constant data values determined during the project scoping and formulation phase (as described in Chapter 3).

The values of all the independent, one dimensional decision variables are set during the input phase of the simulation model. In the case study, this includes all the government measure decision variables (GM1 to GM6). Although the first logistics measure decision variable (LM1) is also an independent variable, it has a higher order dimensionality. All higher dimensional variable values are determined in the transformation phase of the simulation model.

Figure 5.2 shows the logic followed in the input phase. The blue flow chart elements indicate processes and decisions directly influenced by the optimisation model, whilst the purple elements are myopic processes situated within the simulation model. The simulation model first determines whether it has been called by the optimisation model during the archive initialisation step, or during the search part of the optimisation algorithm.

As mentioned in Section 5.1.2, during archive initialisation, random values are generated for each decision variable. The random values are generated subject to the variable definitions listed in Section 3.2.15. If the simulation model is called as part of the search component of the optimisation

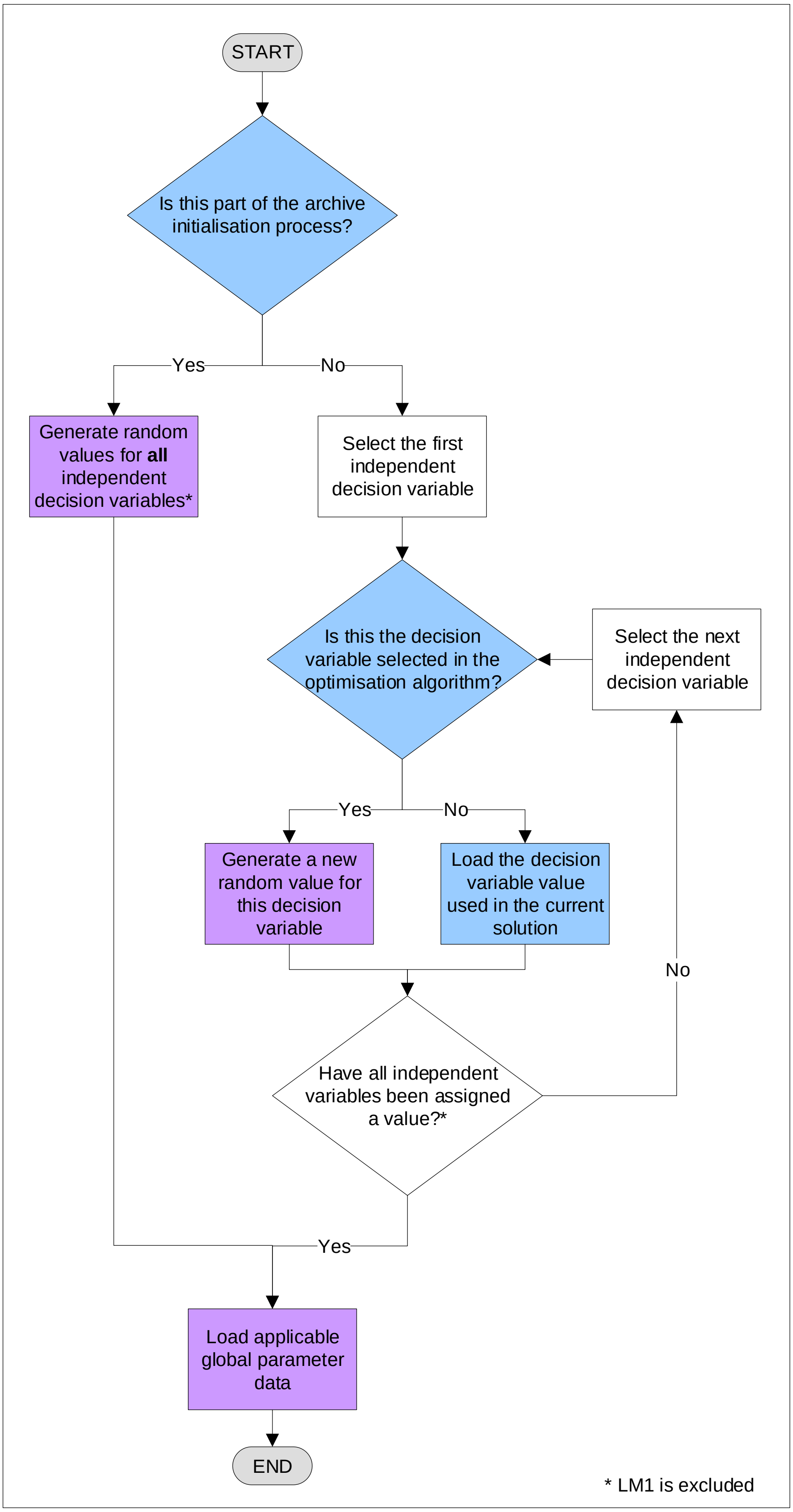


Figure 5.2 Flow chart of the logic in the simulation model input phase

algorithm, the model cycles through every independent, one-dimensional decision variable, checking whether or not this is the decision variable selected by the optimisation model to be modified in the simulation run that generates the *new* solution. If this is, in fact, the variable that needs to change, a new random value is generated subject to the variable's definition, as in Section 3.2.15. For all variables that are not to be changed, the simulation model loads the value for that particular decision variable from the *current* solution.

Certain global parameters are dependent on the settings of the decision variables, for example the route network parameters to load are dependent on the decisions made on network choice (GM1) and on whether new technologies are included or not (GM5). Once all independent, one-dimensional variables have been assigned a value, the correct set of global parameters can be loaded into the model's memory for use during the rest of the simulation model.

5.2.2 Transformation phase

A travel demand model is defined as a model that predicts what travel will be undertaken in response to transport system changes at some future point in time, on the basis of a series of mathematical equations or algorithms that attempt to replicate human decision-making within particular contexts (Behrens, 2007). The transformation phase of the simulation model is a form of travel demand model, where freight demand is assigned in the network (i.e. decisions are made on how the freight will be transported between origins and destinations). This is done subject to one hard constraint – all demand in the network must be met.

The simulation model developed in the FTEMT is loosely based on the premise of the four-step model (summarised in Figure 3.4). However, as one of the inputs to the simulation model is a freight demand origin-destination (OD) matrix (discussed in Section 3.1.3), the trip generation and trip distribution steps are assumed to have been completed already. The transformation phase of the simulation model, thus, only encapsulates the modal split and assignment sub-models. A separate OD matrix, expressing the tonnes of freight of each commodity to be transported between each origin and destination pair, is needed to represent the freight demand trip distribution for each commodity to be included in the model. The full assignment algorithm must be repeated for each commodity. There is, however, only one commodity included in the case study model.

As the purpose of the FTEMT is to develop decision support on freight transport energy management measures, it is necessary to divide freight travel further than merely between various modes of transport. For this application it is also relevant to know the split between all the possible vehicle types making use of various propulsion systems, fuelled by various energy sources, for each mode. This necessitates a seven-tier model hierarchy and a model of high potential dimensionality, as summarised in the following equation:

$$Total\ freight\ demand = \sum_{c=1}^{C}\sum_{o=1}^{O_c}\sum_{m=1}^{M_o}\sum_{r=1}^{R}\sum_{v=1}^{V_m}\sum_{p=1}^{P_v}\sum_{e=1}^{E_p} demand_{comrvpe}$$

where

C = the number of commodities included in the model,

O = the maximum number of freight origins in the model for any of the commodities,

M = the maximum number of modes that can be used to depart any origin,

R = the total number of route segments in the network,

V = the maximum number of vehicles included in the model for any mode,

P = the maximum number of propulsion systems considered per any vehicle type in the model,

E = the maximum number of energy sources that can fuel any of the propulsion systems modelled, and

demand = the demand (in tonnes) that has been assigned in the model to the specific commodity *c*, origin *o*, mode *m*, route segment *r*, vehicle *v*, propulsion system *p* and energy source *e* combination.

The maximum number of assignment decisions to be made by the simulation model can be calculated as the product of the maximum values of C, O, M, R, V, P and E. In the case study, this equates to far more than a million potential assignments for one simulation run. There is no limitation on the number of commodities, objectives, modes, route segments, vehicles, propulsion systems or energy sources that can be included in the model in theory, although the practical aspects of model runtime and data collection might impose such a restriction. The variants of each of these components included in the case study model are discussed in the problem scoping phase in Section 3.1.

Figure 5.3 contains a flow chart of the logic followed in the transformation phase. It indicates the interactions between the various model hierarchy levels, as well as the integration of the multi-dimensional decision variables in this assignment model (indicated in blue). The procedure starts with the first commodity and then, sequentially, works through all the OD pairs that have freight flows of that commodity. For every origin, a list of viable modes departing the origin is determined, subject to

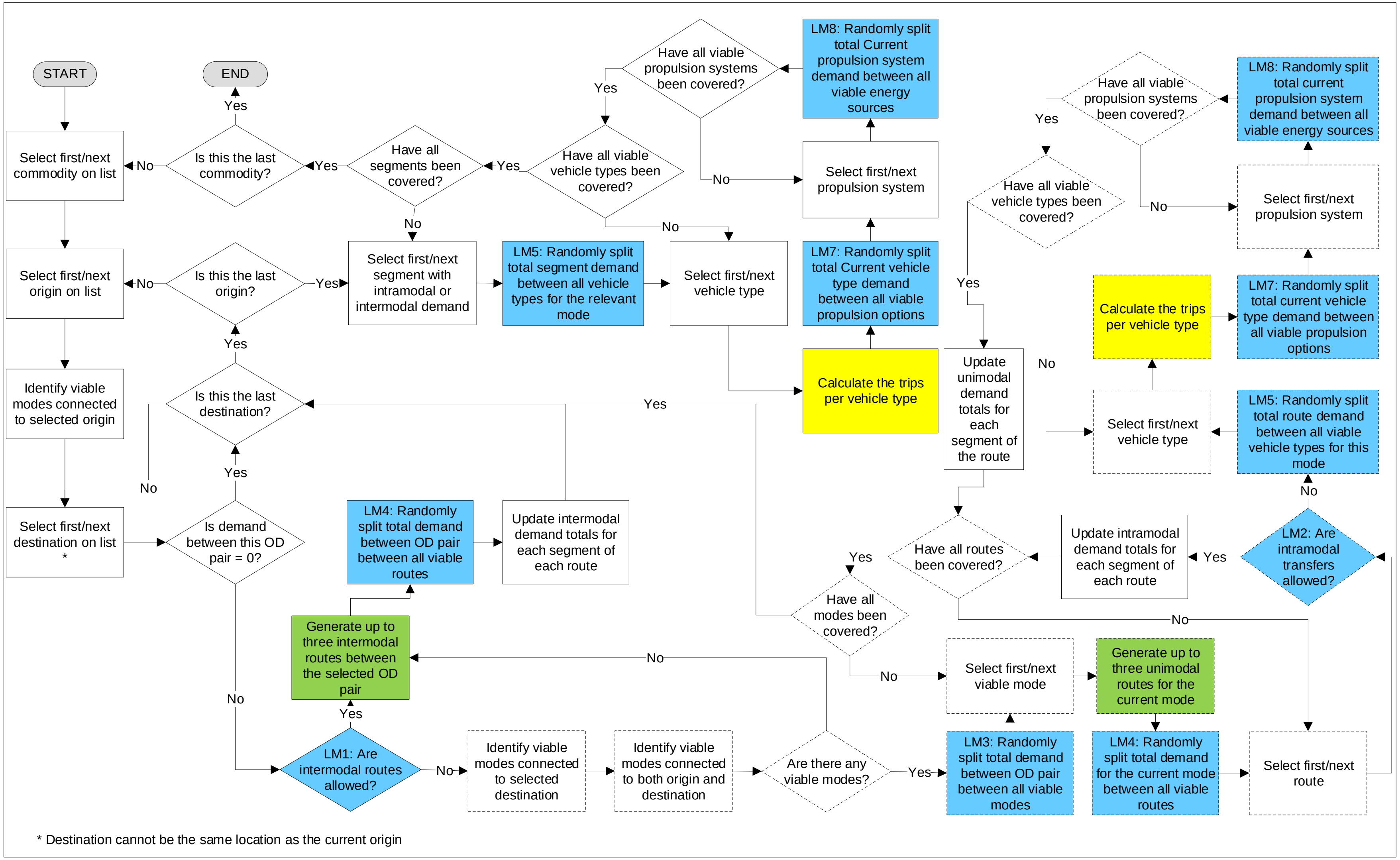


Figure 5.3 Flow chart explaining the simulation model logic for freight demand assignment

the fact that the mode can be used to transport the commodity in question. Once this is known, the demand between the currently selected origin and every potential destination is assessed. OD pairs with no demand are not considered further. If, however, there is demand between an OD pair, the first decision variable's value (LM1) is set by the model.

The value of this decision variable (and all the other multi-dimensional variables) is determined similar to the process followed in the input phase for the one-dimensional variables. If the simulation model is run as part of the archive initialisation process, a completely random value is determined for every dimension of each variable. Otherwise, the decision variable's value is either loaded from the corresponding value for the same dimension in the *current* solution, or a random value per dimension is generated, if the optimisation model selected this variable to be the one to change in this simulation run. A deviation from the process in the input phase is attributed to the dependencies of variables included in this phase of the model. All variables dependent on the decision variable selected for manipulation by the optimisation algorithm are also assigned new randomly generated values over all their dimensions in this phase of the model, even though they were not explicitly selected to be modified by the optimisation algorithm. This is because a change to a higher order variable can impact the range of decisions of its dependent variables and their values need to be regenerated to ensure they fall within these new boundaries.

The model logic followed if LM1 does not allow intermodal transport is indicated by the dashed borders in Figure 5.3. Should the value of LM1 indicate that only unimodal routes are allowed between this OD pair, the algorithm proceeds to identify a list of modes viable to transport goods to the destination at hand. This, in conjunction with the list of modes connected to the origin, is used to check whether there are any modes able to connect both to the origin and the destination. Should no such modes exist, unimodal routing will be impossible and the algorithm defaults to an LM1 setting where intermodal routing is done between this specific OD pair. The values of all decision variables dependent on LM1 now need to change in accordance with this change to LM1.

If there are viable modes connecting both the origin and destination, the next decision variable (LM3) splits the demand between the viable modes. For each mode, up to three unimodal transport routes are developed in the route development algorithm (processes indicated in green in Figure 5.3), which is explained in greater detail at the end of this section. The demand for the mode at hand is then split amongst the three routes, based on the output from decision variable LM4. The algorithm cycles through each route, determining whether intramodal transfers are allowed along the route (decision variable LM2). If intramodal transfers are allowed, the intramodal demand is assigned to each segment along the route and the model moves on to the next viable route. If intramodal transfers are not allowed, the route's demand is split further between the viable vehicle types associated with the currently selected mode (decision variable LM5). For each of these vehicle types, the model calculates the number of vehicle trips required, based on both volumetric and weight-related criteria (processes indicated in yellow in Figure 5.3). The demand, expressed in terms of total transportation weight, assigned to each vehicle type is then split amongst the various propulsion options for that vehicle type (decision variable LM7) and for each of these propulsion systems, its demand is divided amongst the energy sources that can be used to fuel it (decision variable LM8). The conversion of demand to total transportation weight is discussed later in this section. Once all unimodal routes have been assessed and disaggregated in this way, the model moves on to the next mode and the process is repeated. When all modes have been assessed, the process is repeated for all the remaining OD pairs with demand for transport of the commodity at hand.

Where intermodal routing is allowed (based on the value of LM1) between an OD pair, up to three intermodal routes are generated to connect the pair, after which the demand between this OD pair is randomly split between the routes developed (LM4). The total intermodal demand based on this route assignment is added to the total for each segment that has been included in any of the routes. The model then moves on to the next OD pair and, again, assesses whether intermodal routing is allowed or not (LM1). Intramodal decisions are only made on unimodal routes, based on the assumption that if intermodal transport is permissible, intramodal transport will also be allowed. An intermodal route can, thus, be intramodal as well, although this is not necessarily the case.

Upon completion of the demand assignment for all OD pairs, the inter- and intramodal demand per segment needs to be disaggregated further. The total intermodal and total intramodal demand assigned to each segment is tallied together, to form a total demand for transport with the mode associated with that segment (implicit in the route definition). This demand per segment is then further split between vehicle types (LM5), the corresponding propulsion systems (LM7) and energy sources (LM8) in a similar fashion to the disaggregation of the unimodal route demand, and the demand per *comrvpe* combination values are updated. After all segments' demand have been disaggregated, the model moves on to the next commodity to be considered and the whole process is repeated until freight flow demand has been assigned for all the commodities included.

An interesting observation is that, for intermodal routes, the route split is first decided and then the vehicle split is done per segment. There is no deliberate modal split, as the route split decision effectively also represents the modal split for the intermodal demand along the route. Intramodal and intermodal demand can, thus, be summed together per segment, as they are both utilising the same mode of transport and further disaggregation can now be done on the total demand per segment. This is computationally efficient, because the disaggregation has to be done only once for each segment and not for each route that contains the segment. For unimodal routes, however, the modal split is done first, then the route split. Here, the vehicle, propulsion system and energy split for the route is the same for all segments, as it is assumed the same vehicles leaving the origin will complete the entire journey to the route destination. The route generation algorithms used for intermodal and unimodal routing are very similar, although the number of options available for unimodal routes are more limited.

A plethora of routing algorithms exist in the literature. Dijkstra's algorithm (1959) and Tavasszy (1996) are examples of note. The routing algorithm used in the FTEMT is loosely based on Dijkstra's algorithm, but adapted for suitability in the FTEMT. It is not intended to be a newly proposed routing algorithm and can be replaced with any other routing approach that the decision-makers and modellers prefer.

Figure 5.4 provides a flowchart explaining the logic in the FTEMT's routing algorithm. A route is defined as a set of network route segments (i.e. links between nodes in the network) that, sequentially, connect an origin to a destination. Individually numbered segments are modelled with directionality (for example: there will be one segment representing the link between node A as origin and node B as destination and a second segment to connect node B as origin with node A as the destination) and a mode associated with each segment (for example: a road connection between node A and B will be modelled as one segment and a rail connection between the same nodes as a second segment). It is assumed that if two nodes are connected by a mode in one direction, that there will be a connection with the same mode in the opposite direction.

The routing algorithm starts by checking the compatibility of all segments in the network with the commodity, mode and origin in question. A list of the segments that are compatible and, thus, can form part of a route under this configuration is compiled, checking that segments are not added to the list more than once. The short-listed segments are checked to determine whether or not they will result in a dead end. Should this be the case, the segment is no longer regarded as a viable option.

If all segments are discarded, no route can be formed between the OD pair for the mode and commodity at hand. The segments that are, however, fit to be included for further consideration are assessed in terms of the geographical proximity of their end nodes to the final destination on the route (based on a straight-line distance calculated from GPS coordinates). A check is also performed to see if any of the segments complete the route (i.e. reach the final destination). If no segments complete the route and there is only one viable segment, the segment is included in the route and the endpoint of the segment is set as the new origin, from which the process of scanning all segments in the network for viability is repeated. If there is more than one viable segment, the segments are compared in terms of their proximity to the destination in the OD pair. If there is more than one segment that performs equally well, one is randomly selected to form part of the route and this segment's end node is set as the new interim origin for the process to repeat itself. Alternatively, the best segment is chosen to be included in the route, the end-point of that segment forms the new origin and the process is repeated, as previously explained.

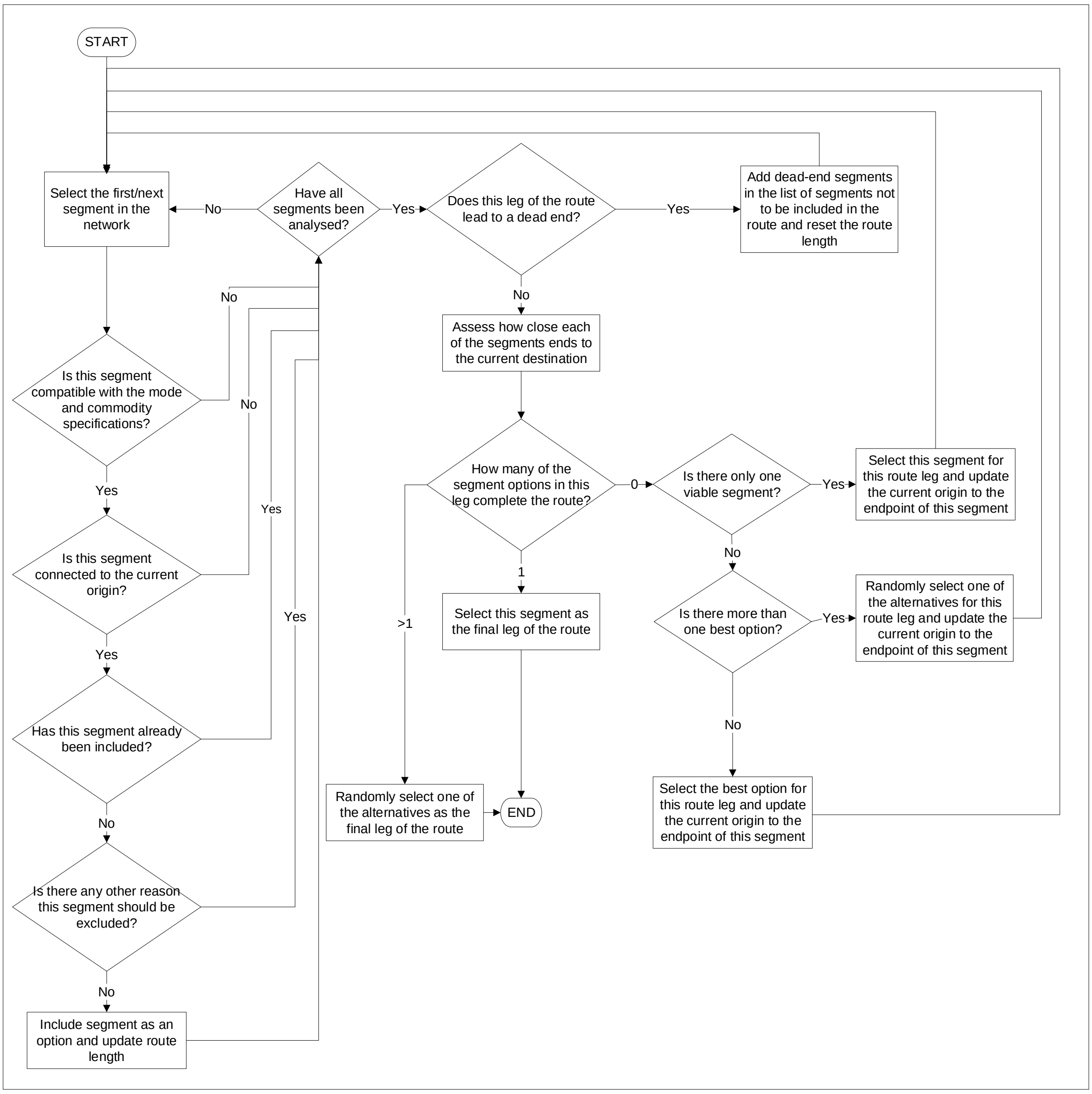


Figure 5.4 Flow chart of the route generation algorithm

If one of the short-listed segments does complete the route, the segment is included in the route and the routing process ends. If more than one segment can complete the route, one of them is randomly selected to be included in the route and the routing process ends. The entire process is repeated, adding a segment to the route in each iteration, until a route is built that can connect the origin to the destination. Routes can consist of any number of segments. If, somewhere along a route, a segment is found that will lead to a dead-end, the model will remove that segment from the route and repeat the search for a viable next segment, with the previous segment's end node as the interim origin. The dead-end segment is marked so that it cannot be considered as a viable option between that OD pair in further analyses.

One of the design parameters in the FTEMT is that the model generates up to three viable routes between each OD pair. This is a user defined parameter and can be changed by the decision-makers and modellers, if required. Figure 5.5 shows the process flow of the development of the three route options. It starts with the first route being generated, as explained in Figure 5.4. Then an analysis on the number of connections to the destination in question is done to determine how many feasible routes can be developed. If only one route can be developed, the routing portion of the model is complete. If more than one route can be developed, one of the segments in route 1 is randomly selected as the point from where route 2 will deviate from route 1. The routing algorithm in Figure 5.4 is used to develop the new portion of the route from this deviation point to the destination. If three routes can be developed, two different deviation points along route 1 are used for the development of routes 2 and 3, respectively. If only two routes are possible, the development of a third route is attempted by choosing a random deviation point along the second route (and not the original route). If no feasible deviations are possible along the second route, the two routes already developed will suffice.

To determine the number of trips required per vehicle (the yellow process in Figure 5.3), the payloads for the vehicle in question need to be determined first. This is where the settings of decision variable GM6 come into play. A random number is generated and compared with the overload prevalence setting for the mode at hand. If the number is smaller than the prevalence setting, the vehicle is deemed to be overloaded, otherwise the maximum potential payload will be calculated. For road freight, the maximum payload for a specific vehicle type is calculated with the following formula:

$$Maximum\ payload = \left(Maximum\ truck\ weight \times (1 + overload\ tolerance)\right) - Tare\ truck\ weight$$

The overload tolerance level is the second level set in decision variable GM6 and represents the percentage by which the truck is overloaded. If the truck is not overloaded, the overload tolerance is zero. For the other modes in question, the input data in the case study model is specified in terms of payload capacity (Section 3.5), reducing the formula to:

$$Maximum\ payload = \left(Payload \times (1 + overload\ tolerance)\right)$$

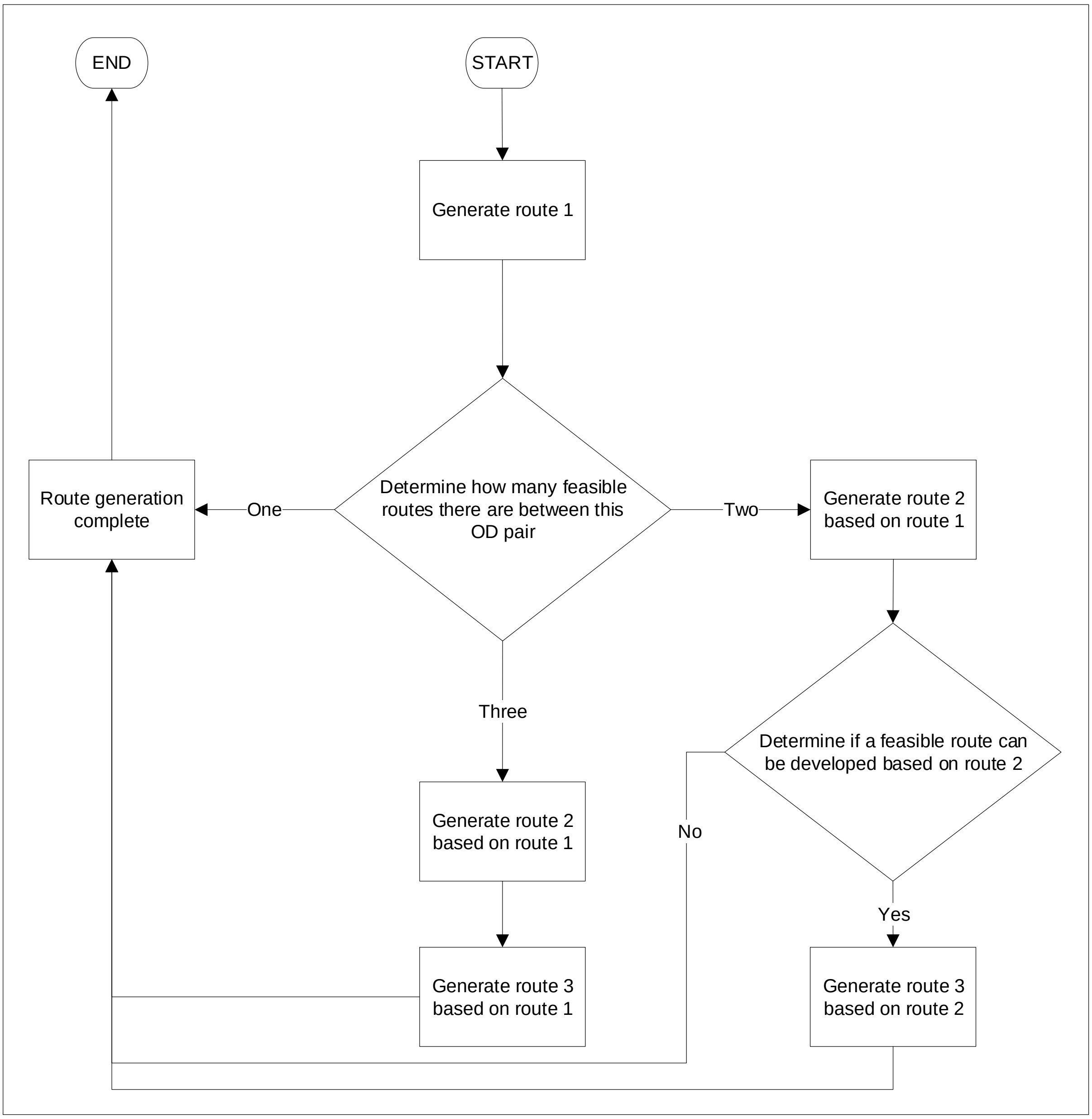


Figure 5.5 Flowchart of the development of the three route options

These payload values represent the maximum weight that the freight loaded onto each vehicle of the selected type can be. The volumetric capacity of each vehicle also needs to be considered, however. The total tonnage assigned to the vehicle type at hand is converted into a volumetric demand by dividing the tonnage with the commodity density value (defined in Section 3.5). This expresses the spatial requirements of the freight that needs to be shipped (in cubic metres).

The vehicle loading regime applicable is determined by picking a random value (dubbed *load regime*), normally distributed around the mean and standard deviation set by decision variable LM6. This value indicates the average capacity utilisation percentage of the vehicle in question and it is assumed that, on average, vehicles are loaded to this level before being sent off. The total number of trips per vehicle type can now be calculated as follows:

$$Total\ trips = \max\left(Weight\ trips; Volume\ trips\right)$$

where

$$Weight\ trips = \mathrm{floor}\left(\frac{total\ demand\ in\ tonnes}{maximum\ payload \times load\ regime}\right)$$

$$Volume\ trips = \mathrm{floor}\left(\frac{total\ demand\ in\ m^3}{volumetric\ capacity \times load\ regime}\right)$$

The total number of trips per vehicle type are, thus, based on the higher amount when the number of trips required, based on a weight dependent calculation, is compared to the number of trips required based on a volume dependent calculation. Put differently, this implies that the trips are calculated based on the limiting factor between weight and volumetric capacity. The *floor* operator in these equations indicate that, should there be a fraction remaining when the demand has been split into trips, the model will round down the number of trips to the nearest integer. Trips can only be expressed as integers. The remaining demand can then be added to the following vehicle type's demand, before that demand is split into trips. When the number of trips has been calculated for all vehicle types, the final remainder adds one extra trip to the last vehicle type's trip count, even though the vehicle is not loaded to the same capacity as the other vehicles of the same type.

Next, it is necessary to calculate the total mass that needs to be transported per trip, i.e. the payload tonnage needs to be combined with the vehicle weight to determine the total weight that will be moved along the route. Depending on whether the weight or volumetric capacity is the limiting constraint when the vehicle payloads are determined, one of the following formulae is used to calculate the total transportation weight:

$$Total\ vehicle\ weight_{weight-based} = \left(maximum\ payload \times load\ regime\right) + tare\ weight$$

$$Total\ vehicle\ weight_{volume-based} = \left(\frac{volumetric\ capacity \times load\ regime}{commodity\ density}\right) + tare\ weight$$

$$Total\ transportation\ weight = Total\ trips \times Total\ vehicle\ weight$$

The final vehicle loaded at lower capacity to accommodate the remainder of the freight's total weight is calculated as the product of the weight of the remainder and the tare mass of the vehicle that it will be transported with. This value is added to the total transportation weight.

For rail transport, the number of trips per vehicle type and the total transportation weight are calculated per wagon using the formulae described. The wagons are grouped into train sets after the propulsion system (locomotive) assignment has been done, using the following formula:

$$Number\ of\ locomotives = \mathrm{ceil}\left(\frac{total\ transportation\ weight}{locomotive\ power}\right)$$

where *locomotive power* represents the maximum load carrying capacity (in tonnes) of the locomotive travelling at 50 km/h. The operator *ceil* indicates that any remainder will be rounded up to the nearest integer, implying that an extra locomotive with be allocated to the route. The locomotives' tare mass is added to the total transportation weight once the number of locomotives to be used is known.

When all assignments have been made, the total transportation weight per *comrvpe* combination (in tonnes) is multiplied with the length of each route segment (in kilometres), yielding a tonne-kilometre (tkm) value per combination to be used in the output phase calculations. These values, however, do not represent the full complement of transportation in the network, because the manoeuvring of empty vehicles to ensure adequate stock of the required transportation vehicles has not yet been factored in. There has to be enough vehicles of a certain type at every node in order to fulfil the network assignment's trips. Should more vehicles need to depart from a node than there are vehicles arriving at that node, the model needs to rebalance the vehicle counts by adding empty trips to reposition vehicles to service all trips. Figure 5.6 displays the logic of the empty trip assignment algorithm.

The algorithm starts by tallying the total number of vehicles of a specific configuration arriving at and departing from every node in the network. If there are more arrivals than departures at a node, the node is considered a surplus node. Conversely, if more vehicles need to depart the node than what enters it, the node is a net demand node. This is determined for every commodity, origin, mode, vehicle, propulsion system and energy combination per node. Route information is not relevant for these combinations, as new routing assignments need to be made for the empty trips. The premise behind the empty trip assignment algorithm is to balance supply and demand over the network. Vehicles from supply nodes are routed to demand nodes until equilibrium is reached. Each node's supply and demand of a specific vehicle configuration is effectively treated as a zero-sum game.

The model cycles through all nodes and all vehicle combinations per node. If the node has a surplus for the vehicle combination in question, the nearest neighbour with demand for that combination is identified and demand and supply balanced between the two nodes. This means that either all the demand is satisfied if the supply node has more vehicles than demanded, or all supply is cleared if there is greater demand for vehicles than what is available for supply. The supply and demand values per node are updated accordingly. It is possible that there might still be unmet supply or demand in one of the nodes when this assignment has been completed and a new nearest neighbour with outstanding demand will be sought for the process to repeat itself. If supply equals demand, both nodes are in equilibrium for this vehicle combination and will not be considered for further empty trip assignments.

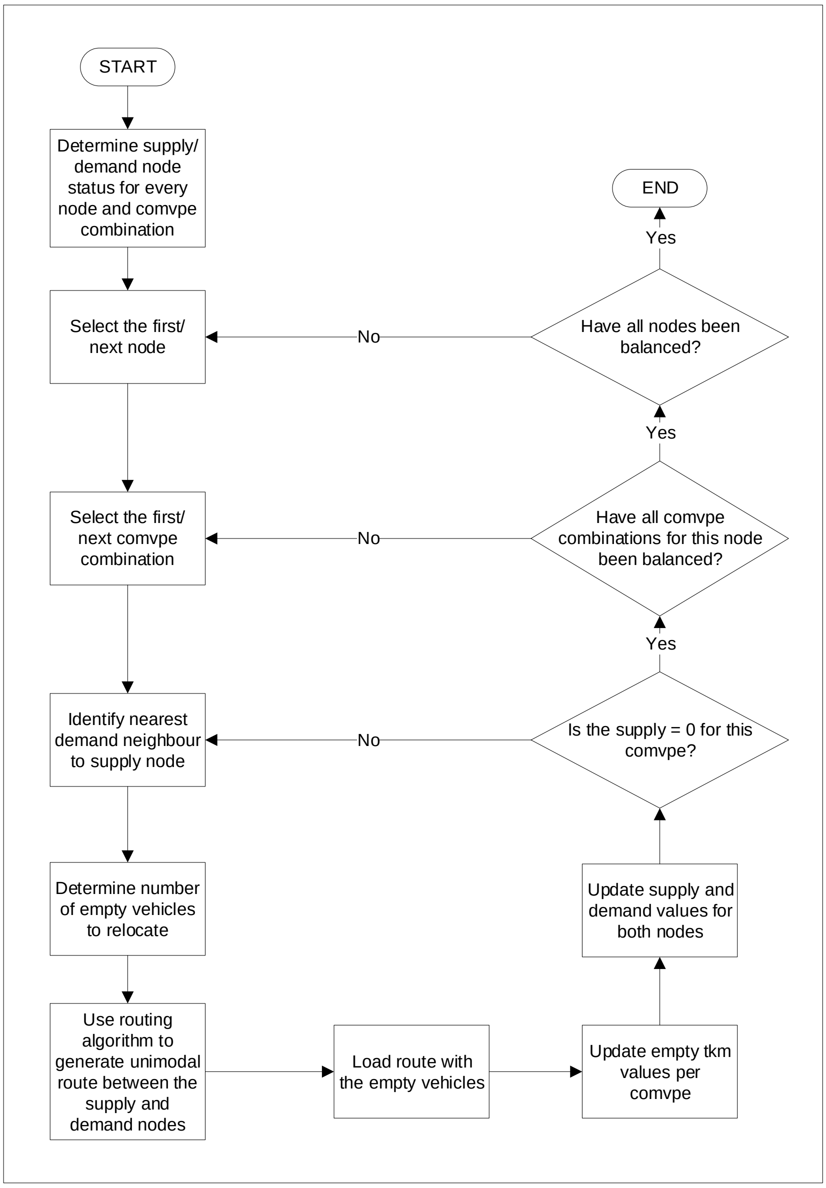


Figure 5.6 Flow chart of the logic to calculate empty trips

The unimodal routing algorithm described in Figure 5.4 is used to generate the route that the vehicles which need to be relocated will take. The tare vehicle weight is multiplied by the length of each segment and by the number of empty vehicle trips along this route, to determine the total empty tonne-kilometres (tkms) added to the network assignment. The total empty tkms calculated are added to the loaded freight tkms in order to determine the total tkms travelled to realise the network assignment in this instance of the simulation model. This is the final output of the transformation phase, on which the calculations in the output phase will be based.

It is interesting to note that empty running is not an explicit decision variable that can be manipulated in the FTEMT, however, decisions on network design (GM1), vehicle park restrictions (GM2), new technology (GM5), overload tolerance (GM6), intermodality (LM1), intramodality (LM2), modal split (LM3), vehicle split (LM5), vehicle loading regimes (LM6), propulsion system split (LM7) and the energy split (LM8) all impact the total amount of empty running imposed on the network, ultimately affecting the performance assessment of the network assignment in the output phase. If the combined impact of these decision variable settings result in large numbers of empty trips, the solution will be penalised correspondingly in terms of the performance criteria, making this an implicit decision variable.

5.2.3 Output phase

The output phase of the simulation model in the FTEMT serves to provide a performance assessment of the network assignment determined in the transformation phase. These values are used by the optimisation model to evaluate dominance between solutions and, therefore, correspond to the objective function definitions developed in Section 3.2.16.

The data generated in the transformation phase (a tkm per *comrvpe* combination value) is highly disaggregate, but the hierarchical nature of the data captured enables aggregation at higher levels as needed in the performance calculations of each of the three objectives (as specified in the formulae developed in Section 3.2.16).

Three output values (in the case study model) are output for each simulation run – an *Environment* value, an *Economic* value and a *Social* value. The three output values are initially calculated in their own dimension, but to avoid dimensionality bias in the dominance estimates of the optimisation algorithm, indexing is applied to the values of each objective. The archive values available for each objective are used to scale the index, where the highest objective value amongst the *current* solution and the archive solutions is set to the maximum value of 100 and the lowest to the minimum value of 0. Each objective is scaled independently. Care needs to be taken that the order of magnitude of the scores for different solutions are adequately captured during this indexing exercise – a single unit increase should represent the relative change in values on the original scales appropriately.

5.3 Addressing the Problem Complexity

The formulation of the FTEMT model, as described in this chapter, successfully addresses the problem complexities highlighted in Sections 1.2 and 1.6. The conceptual design and flow of information between model components is depicted in Figure 5.7. Decisions impacting the decision variable (energy management measure) values are made in the optimisation model and the values are transferred to the simulation model. The first two phases of the simulation model (input and transformation) effectively converts this measure combination into a freight transport assignment over the network and produces the resultant, disaggregate tonne-kilometres travelled in the network by the various vehicle configurations. This tonne-kilometre data is converted to scores over each of the multiple objective functions in the final (output) phase of the simulation model. The objective function assessment values are transferred to the optimisation model, where they are used to determine the quality of the solution generated. Based on this quality assessment and a relative comparison to other solutions already explored, the optimisation model makes new decisions in terms of the decision variable values and the process continues until the optimisation model terminates the search.

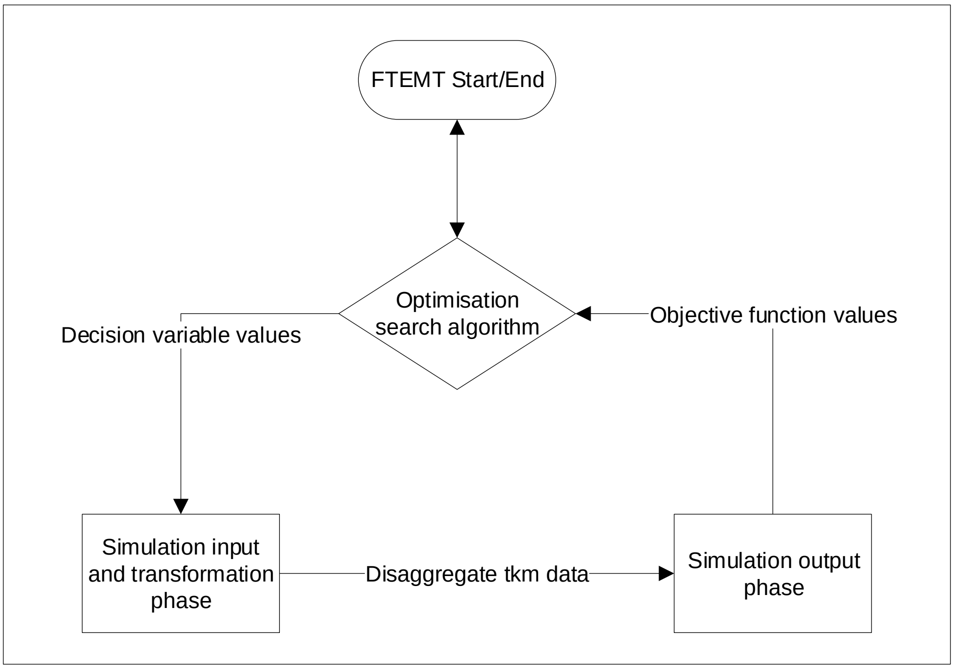


Figure 5.7 Conceptual design of the FTEMT

It is important to note that decisions are only made in the optimisation model, while there are two data transformation steps in the simulation model. It is this two-step structure of the simulation that allows the model to evaluate the impact of the measure combinations generated by the optimisation model, rather than of individual measures, because the tonne-kilometre values calculated in the first transformation step represents the simultaneous influence of all measures on the network. The nett impact of this measure combination is then assessed in the second data transformation step. This answers research question 2.7 (how to allow the model to formulate and explore measure combinations).

Converting all decisions made in terms of measure values to a tonne-kilometre value on which the objective functions are assessed, ensures consistency in evaluating different measure combinations and a host of diverse measures, because the assessments are comparable and are performed in the same manner for all combinations evaluated. Research questions 2.2 (how to accommodate measures of all types and scope into one single model) and 2.9 (how to fairly compare the impacts of measures) have, thus, been addressed.

Measures are scrutinised to determine whether they impact the boundaries of the network assignment (in which case they influence the input phase of the simulation model), the network assignment (influencing the transformation phase of the simulation model), or the estimation of the objective function values (influencing the output phase of the simulation model). New measures will be modelled in a similar fashion to the existing measures of a similar nature and their inclusion will impact either the network assignment totals or the assessment of the network assignment. This model structure is generic enough to conceivably accommodate unknown, future measures as well, answering research question 2.3 (how to keep the model generic so that unknown, future measures can also be accommodated). There is no theoretical limit on the number of measures that can be added to the model specification. The scale of the simulation will keep on increasing as the number of measures included increases, but it will still produce a single tonne-kilometre network assignment that feeds into the objective function assessment. This speaks to research question 2.4 (how to include any number of measures). The blueprint for modelling various distinct measure types and their impacts has been developed in the case study model. The measure categorisation in Section 3.2 demonstrates that basically all freight transport energy management measures fall into one of the typologies modelled and it is expected that future measures could also be classified in this way.

Breaking up the network assignment into a hierarchical, stepwise assignment allows the simulation model to take measure dependencies into account. This design feature speaks to research questions

2.6 (how to model the interaction between measures) and 2.12 (how to account for knock-on effects of measure implementation). The dependencies between measures make it impossible for the model not to take the repercussions of a change in one variable on the other variables into account. Double counting of measure impacts (research question 2.11) is also avoided, because the sequential network assignment only estimates the assignment of demand to every commodity, origin, mode, route, vehicle, propulsion system and energy combination once.

The simulation model can only generate random values for the measures that need to be modified subject to the mathematical measure definitions summarised in Section 3.2.15. Values can, however, fall anywhere within the ranges specified, allowing a new variable measure impact to be modelled in every simulation instance, as required in research question 2.5 (how to allow for variable implementation levels per measure). The simulation model only requires the randomly generated value to proceed, allowing both discrete and continuous measures to be included in the model, answering research question 2.8 (how to deal with both continuous and discrete variables).

The simulation output phase can output any number of objectives related to the network assignment (tkm value). As there are multi-dimensional outputs generated by the simulation model, the modelling of multiple objectives in the optimisation algorithm is enabled. The nature of the optimisation algorithm implemented (AMOSA) is suitable for multi-objective decision-making. Research question 2.13 (how to deal with multiple objectives) has, thus, been adequately addressed.

5.4 Verification of the Solution Procedure

The standardised operations research process indicates that verification of the solution procedure be performed as part of the solution procedure development step. “Verification is the task of ensuring that the model behaves as you intended; more colloquially, it’s known as debugging the model” (Kelton *et al.*, 2004). To some degree, getting the model to run is the first step in verifying the solution procedure. This requires sorting out coding errors in terms of syntax and typographical errors. It is more difficult to find errors in the logic embedded in the code. To do that, tests need to be designed and developed that will ferret out unintended offending interactions and the simple modelling mistakes.

There are two basic approaches for testing simulation software: static testing and dynamic testing (Fairley, 1976). In static testing, the computer programme is analysed to determine if it is correct by using techniques such as structured walkthroughs, correctness proofs and examining the structure properties of the programme. In dynamic testing, the computer programme is executed under different conditions and the values obtained (including those generated during the execution) are used to determine if the computer programme and its implementations are correct. The techniques commonly used in dynamic testing are traces, investigations of input-output relations using different validation techniques, internal consistency checks and reprogramming critical components to determine if the same results are obtained. If there are a large number of variables, the numerical values of some of the variables might be aggregated to reduce the number of tests needed, or certain types of design of experiments might be used (Kleijnen, 1987). Sargent (2011) states that the primary techniques used to determine that a model has been programmed correctly are structured walkthroughs and traces. Although these approaches are suggested in the simulation modelling domain, they are also relevant for other types of computer programming models.

Verification was done repeatedly during coding of the case study model. Random numbers generated were checked to ensure that they comply with their design specification. Where splits had to be made on specific hierarchical levels (for example a modal split), checks were performed to ensure that the sum of the parts added up to the whole (this was done through structured walkthroughs). Totals of splits at lower hierarchical levels were aggregated and compared to the split values at the higher level, to ensure that the total demand assignment did not exceed the demand stipulated in the freight demand table supplied by Havenga (Section 3.1.3). Where complex calculations were modelled, the results from the coded formulae were compared to the results of offline calculations by hand, to ensure accuracy of the coded version. Input-output analysis was used to determine whether all decision variables actually impacted the final objective values and to check whether the magnitude and direction of changes had the expected impact (logic test).

The optimisation model was verified with the same techniques. The dominance and acceptance probability calculations were compared to offline answers to ensure accuracy. Furthermore, walkthroughs were done to make sure that the algorithm applied the cooling schedule, reannealing cycles and decision variable modifications as intended. Input-output analysis was used to determine whether good solutions actually replaced poor solutions, evolving the Pareto set over time.

Sargent (2011) indicates that while checking the correctness of a computer programme and its implementation, the modeller should be aware that errors found may be caused by the data, the conceptual model, the computer programme, or the computer implementation. For this reason, care was taken to ensure accuracy of the data to be used in the model and data entries were double-checked for correctness.

The FTEMT was coded in Matlab R2013a Student Version and run on a computer with an Intel® Core™ i7-3667U CPU @ 2.00 GHz and 8 Gb installed random access memory with a run-time of 120 hours to complete one instance of the case study model.

5.5 Chapter Summary

This chapter provided a detailed description of the logic followed in the FTEMT. The interaction between the optimisation model and the simulation model was made clear, as well as the integration of the decision variables into both models. The model logic is clear and transparent and it is easy to see how each of the decision variables influence the final output produced. The search method followed in the optimisation algorithm is clearly defined and the exploration of the search space transparent, addressing research question 2.17 (is the model transparent and tractable).

Research questions 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 2.8, 2.9, 2.11, 2.12, 2.13 and 2.17 have been addressed in this chapter, serving to demonstrate that the FTEMT is successful in dealing with the problem complexity identified in the problem statement in Section 1.2. Verification of the solution procedure developed was also discussed in this chapter.

6 The Final Decision Stage

The final decision stage of the standardised operations research process, described in Section 1.5 and Appendix B, comprises validation of the model, sensitivity analysis and selection of the solution that will be implemented. Figure 6.1 is a graphical representation of how verification and validation relate to model development. This representation was developed by Sargent (2011). In this figure, the problem entity is the system to be modelled, the conceptual model is the mathematical, verbal or logical representation of the problem entity developed for a particular study and the computerised model is the conceptual model implemented on a computer. The conceptual model is developed through an analysis and modelling phase, the computerised model is developed through a computer programming and implementation phase and inferences about the problem entity are obtained by conducting computer experiments on the computerised model in the experimentation phase.

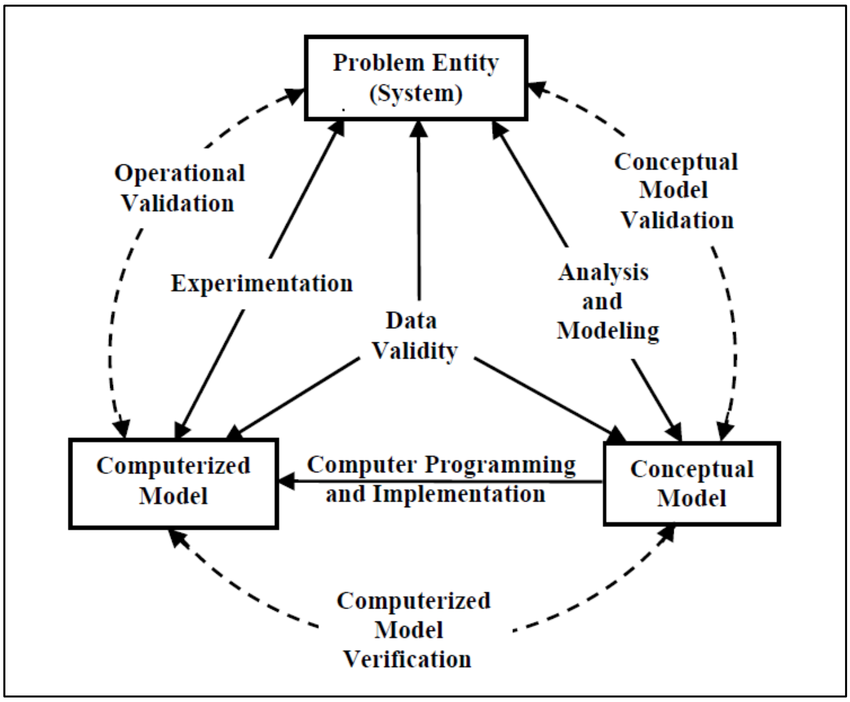


Figure 6.1 Simplified version of the modelling process (Sargent, 2011)

Conceptual model validation is defined as determining that the theories and assumptions underlying the conceptual model are correct and that the model representation of the problem entity is reasonable for the intended purpose of the model (Sargent, 2011). Computerised model verification is defined as assuring that the computer programming and implementation of the conceptual model is correct. Operational validation is defined as determining that the model's output behaviour has sufficient accuracy for the model's intended purpose over the domain of the model's intended applicability. Data validity is defined as ensuring that the data necessary for model building, model evaluation and testing and conducting the model experiments to solve the problem are adequate and correct.

Section 5.3 serves as conceptual validation of the solution procedure developed for the FTEMT. Operational validation, on the other hand, is discussed in this chapter (Section 6.1), which is followed by an exposition of the results generated by the FTEMT (Section 6.2). The chapter concludes with a discussion on selecting a solution for implementation by the decision-makers (Section 6.3). Both computerised verification and data validity have been addressed in Section 5.4 of Chapter 5. As sensitivity analysis can be categorised as a validation technique (Sargent, 2011), it is dealt with in a sub-section of Section 6.1.

6.1 Operational Model Validation

A model should be developed for a specific purpose (or application) and its validity determined with respect to that purpose (Sargent, 2011). Operational validation is, thus, performed to confirm that model outputs are fit for purpose. If the purpose of a model is to answer a variety of questions, the validity of the model needs to be determined with respect to each question. For the FTEMT, validation is done in terms of its two stated objectives. Firstly, the model should find a Pareto set of solutions as close as possible to the true efficient frontier. Secondly, this needs to be achieved by exploring different energy management measure combinations. The premise behind the FTEMT is that there are certain measure combinations that outperform others and the model needs to be shown to illuminate these combinations, if they exist, or serve as proof that the premise was incorrect.

6.1.1 Development of the Pareto front

The FTEMT algorithm starts by generating an initial archive of 30 completely random solutions (i.e. the measure settings for each of the 14 decision variables are all random in each run). This set of solutions forms the full initial archive. Upon inspection it is found that certain solutions dominate others. The algorithm removes the dominated solutions from the full initial archive and, in the case study model utilising the second a priori parameter configuration discussed in Section 5.1.1, this yielded a non-dominated initial archive of 13 non-dominated solutions. Figure 6.2 shows the three-dimensional objective values of the initial archive. Each data point represents a solution in the full initial archive, but the solid, filled data points represent the non-dominated solutions remaining in the initial archive. The non-dominated initial archive is, at this point, the nearest approximation to the true Pareto frontier. For greater definition and clarity, Figure 6.3 shows two-dimensional views of the Pareto front.

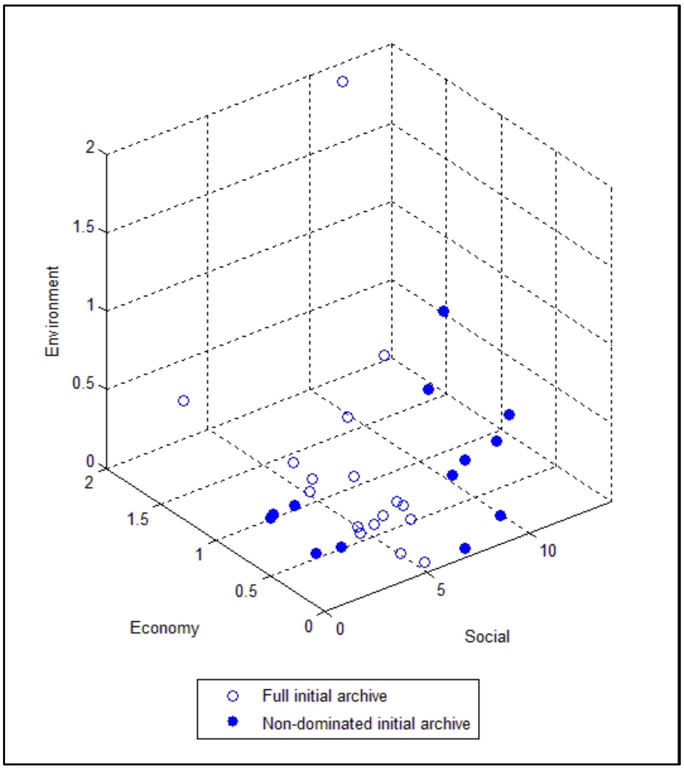


Figure 6.2 3D view of the Pareto front developed in initial archive generation step

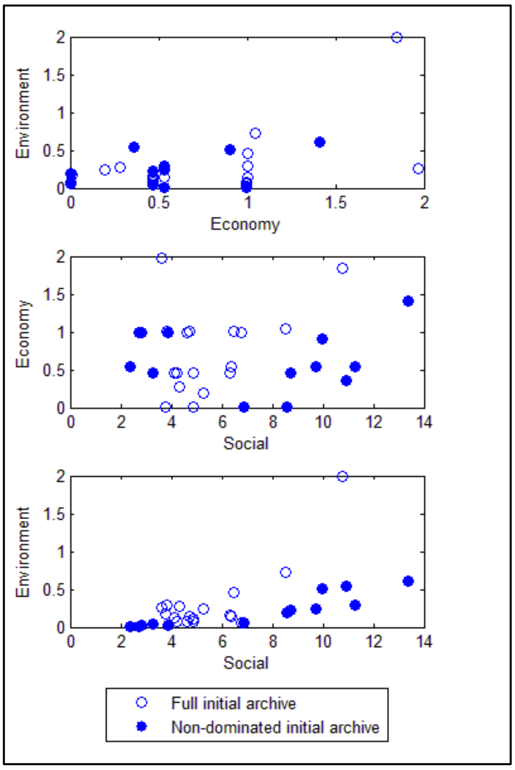


Figure 6.3 2D views of the Pareto front developed in initial archive generation step

A hill-climb algorithm is then applied to each solution in the initial archive, in order to locally search the space around each solution, potentially enhancing the quality of the solutions in the archive. The algorithm did not manage to strictly improve upon any of the solutions in the archive, although 182 solutions were explored. Figure 6.4 and Figure 6.5 display the solutions explored in the hill-climb algorithm (hollow light blue data points) alongside those of the initial archive. The figures clearly show a great improvement in exploration of the search space when the hill-climbing is performed. Should the AMOSA algorithm have been modified to accept all non-dominant solutions found by the hill-climb algorithm, instead of only keeping dominating solutions, 131 new solutions would have been added to the initial archive, increasing the density of the initial front. This new front is displayed as the solid light blue data points in Figure 6.4 and Figure 6.5. For posterity, however, the case study version of the FTEMT followed the specifications in the AMOSA algorithm, rendering the post-hill-climb archive exactly the same as the initial archive, because the algorithm specifies that only dominating solutions are to be used to replace dominated archive solutions.

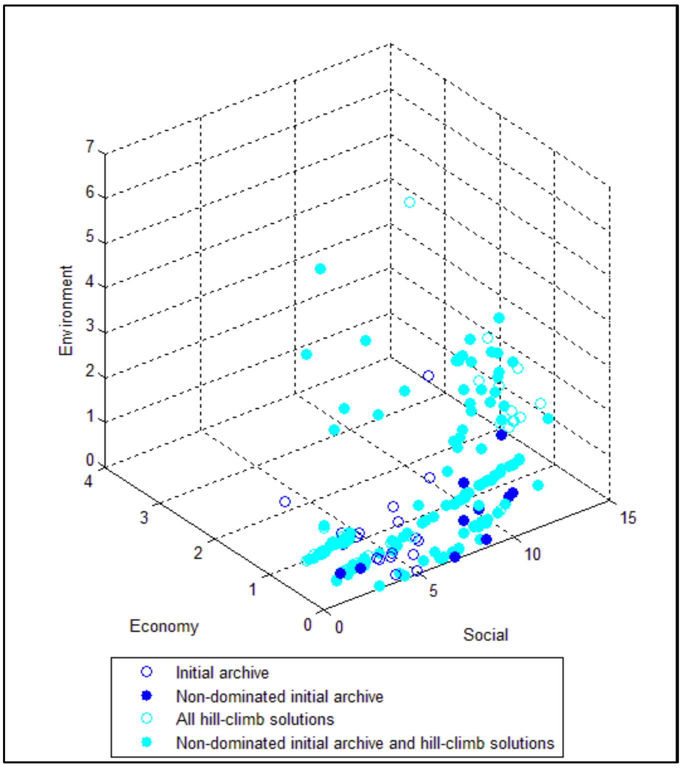


Figure 6.4 3D view of the initial archive and hill-climb solutions explored

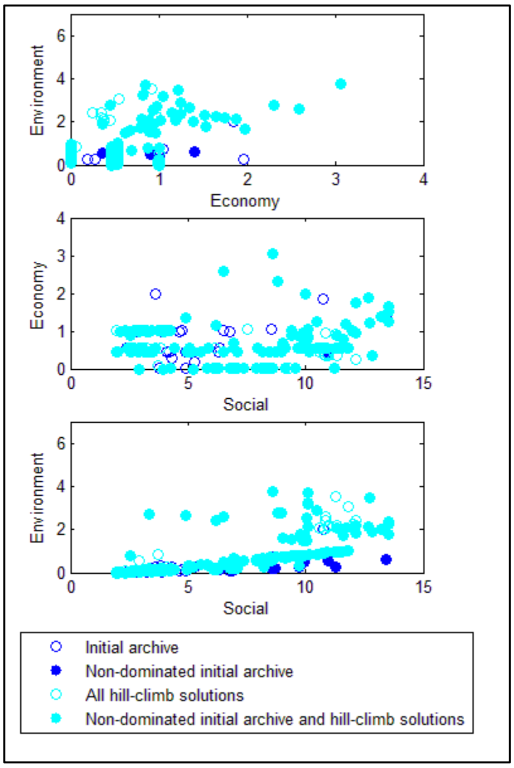


Figure 6.5 2D views of the initial archive and hill-climb solutions explored

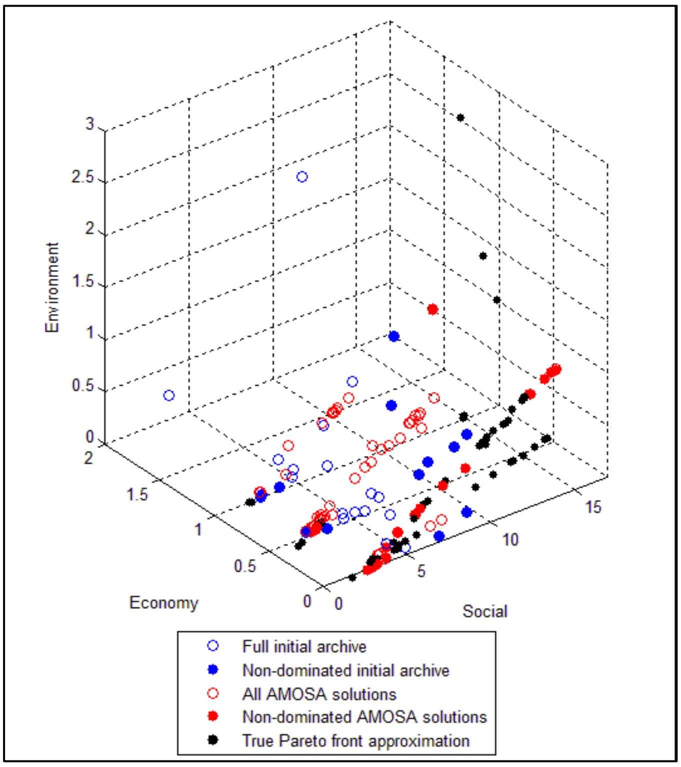


Figure 6.6 3D view of AMOSA Pareto front compared to the initial archive and the true front approximation

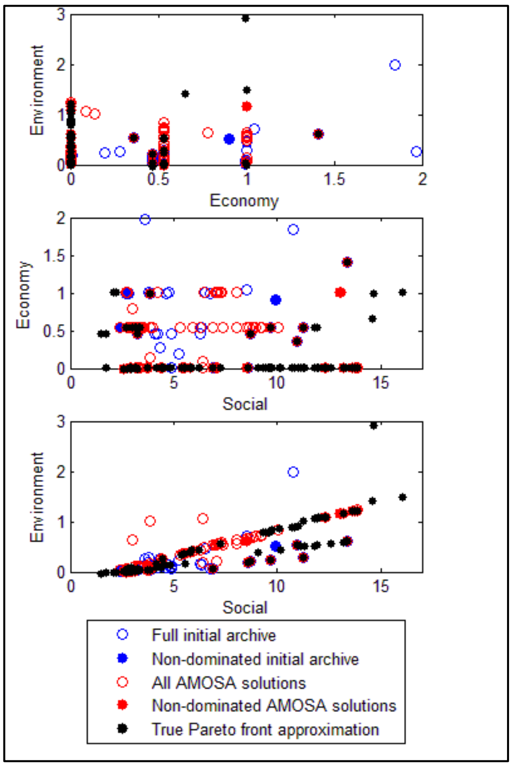


Figure 6.7 2D views of AMOSA Pareto front compared to the initial archive and the true front approximation

The AMOSA algorithm performed 77 perturbations, yielding a Pareto front of 35 non-dominated solutions. Figure 6.6 and Figure 6.7 show the AMOSA Pareto front as solid red data points. The hollow red data points are the dominated solutions explored by the algorithm. The graphs also display the approximation of the true Pareto front, discussed in Section 5.1.1, in black, and the initial archive in blue.

The initial archive is developed using pure exploration. Comparing this with the front produced by the AMOSA algorithm, which is a balanced mixture of exploration and exploitation, it is evident that solutions on the AMOSA Pareto front are more closely aligned with each other than that of the initial archive. This is in line with expectations. The AMOSA Pareto front also succeeded in generating a frontier a lot closer to the approximate true frontier. Conversely, the hill-climb algorithm is an example of a pure exploitative algorithm. When all the non-dominated solutions generated by the hill-climb algorithm are compared to the approximate true frontier, it achieves a purity score of 2%. The AMOSA algorithm, on the other hand, scores 68% and was, thus, able to find significantly more good solutions in far fewer iterations. It appears that the balance between exploration and exploitation in the AMOSA algorithm outperforms both a pure explorative and a pure exploitative approach.

Inspection of the two-dimensional views of the Pareto front shows that the most pronounced trade-off exists between the environmental and social objectives. An improvement in terms of the environmental objective generally has a negative impact on the social objective and vice versa. This result is not unexpected, considering the problem formulation specified in Section 3.3.1 and Section 3.3.3 – the modes with the worst environmental performance are the best performers in terms of the job criterion used to assess the social objective score and vice versa. Correlations between the objective functions support this: the correlation between the environmental and social objectives is 0.9, while the correlation between the environmental and economic objective is 0.01 and between the economic and social objectives 0.17. This can be seen as another form of validation that the model behaves as expected. The figures also show that the front is probably not a continuous function, but rather a piece-wise continuous function. Complicated functions such as this are highly amenable to the use of metaheuristics, validating the choice of modelling tool selected for use in the FTEMT in Chapter 4. It is postulated that the lack of correlation between the economic objective and the other objectives is related to the piece-wise discontinuities of the Pareto front.

The output from the FTEMT serves as proof that there are solutions (i.e. measure combinations) that outperform (dominate) others. Visual inspection reveals that the front does appear to form a boundary to the search space. Moreover, the graphs serve as proof that the search space is explored by the FTEMT algorithm and that the algorithm progresses towards finding the efficient frontier. Given enough iterations and sufficient balance between exploration and exploitation, it is expected that the algorithm will eventually explore the entire search space and identify the true efficient frontier. However, this may not be practical, nor necessary. It is impossible to verify whether the true frontier has been estimated, as this value is unknown and cannot be definitively calculated. In this type of practice, it is acceptable to settle for a good approximation of the true frontier and the FTEMT provides that. As explained in Section 4.1, the search space for the problem at hand is infinite. Outputs from the FTEMT (Figure 6.6 and Figure 6.7) show that the tool can approximate the best-known frontier well in only 77 iterations.

The purpose of the FTEMT is to provide decision support on what freight transport energy management measure combinations to implement. Even if the absolute best combination cannot be identified with complete confidence, there is enough evidence to show that the model does explore the search space thoroughly enough to identify and converge towards better solutions. These good solutions provide useful insight for the decision-makers and are practicable. It is not humanly possible to make decisions based on an unlimited amount of information. The true value-add of the FTEMT is that it whittles down the number of alternatives that decision-makers need to consider to a manageable extent, without a loss in fidelity, scope and complexity of the alternatives. Hillier and Lieberman (2010) suggest that the test of the practical success of an operations research study should hinge on whether it provides a better guide for action than can be obtained by any other means. Rardin (1998), in turn, suggests that a model is validated if it can be argued that conclusions drawn from the model are meaningful enough to infer decisions for the person(s) with the problem. The FTEMT develops a Pareto set of good freight transport energy management strategies, whilst taking the underlying complexities associated with the formulation of such strategies into account. This provides decision-makers with a finite set of options to debate and consider, in contrast with the vast sea of information that decision-makers would otherwise be confronted with.

6.1.2 Exploration of measure combinations

In multi-objective optimisation, a distinction is made between the search (decision) space and the objective space. The decision space refers to the space containing the parameter values for the decision variables in the model, whereas the objective space relates to the objective function values of the model. This concept is illustrated in Figure 6.8. The vector *F* is a cost function relating the decision variable values in the decision space to the objective function values in the objective space (Talbi, 2009). The evaluation and comparison of solutions occurs in the objective space, whilst the search for the optimal decision variable values occurs in the decision space (also named the solution space). The Pareto front resides in objective space. Every solution in the objective space can be mapped to a set of decision variable values in the decision space. Figure 6.9 showcases the values set for each decision variable in each perturbation of the case study AMOSA model. This graph serves as evidence that the model does, in fact, explore different energy management measure combinations in the various perturbations. Not all of the combinations explored yield dominant solutions, proving that some combinations outperform others and that the model is able to find these good combinations. The FTEMT is, thus, validated in terms of its second objective, as well.

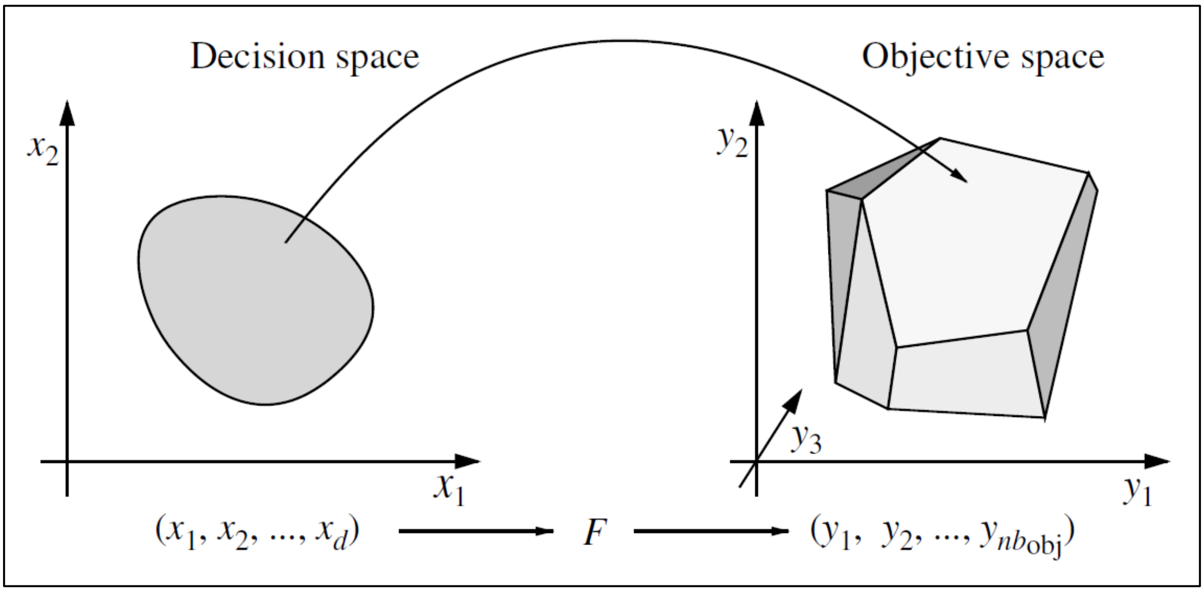


Figure 6.8 Decision space and objective space in a multi-objective optimisation problem (Talbi, 2009)

The data displayed in Figure 6.9 shows that the model sometimes gets caught in a local area of the search space, where the algorithm does not have the ability to generate new measure combinations that are accepted and it reverts back to the current solution's measure settings. These periods do not last long, however, before the model is able to explore a different measure combination. Looking only at the measure combinations that correspond to the solutions included in the Pareto front (Figure 6.10), no two combinations have the same values across all variables. The Pareto set, thus, consists of unique measure combinations. The first nine solutions in the Pareto set survived from the initial archive and the rest were added by the AMOSA algorithm. The random, explorative nature of the initial archive's combinations, in contrast with the AMOSA solutions that appear to be formed by a more structured approach, is evident in Figure 6.10.

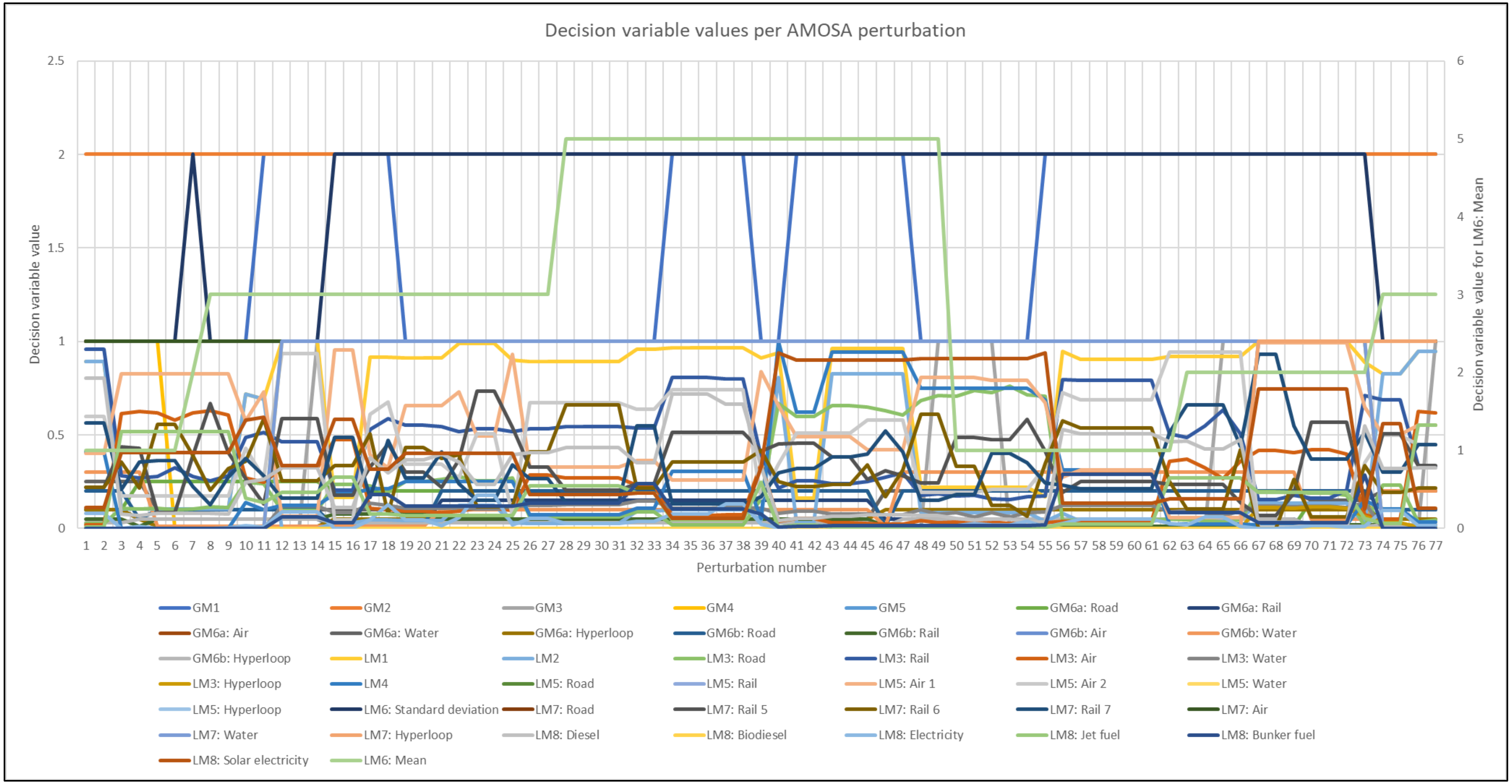


Figure 6.9 Decision variable values applied per AMOSA perturbation in the case study model

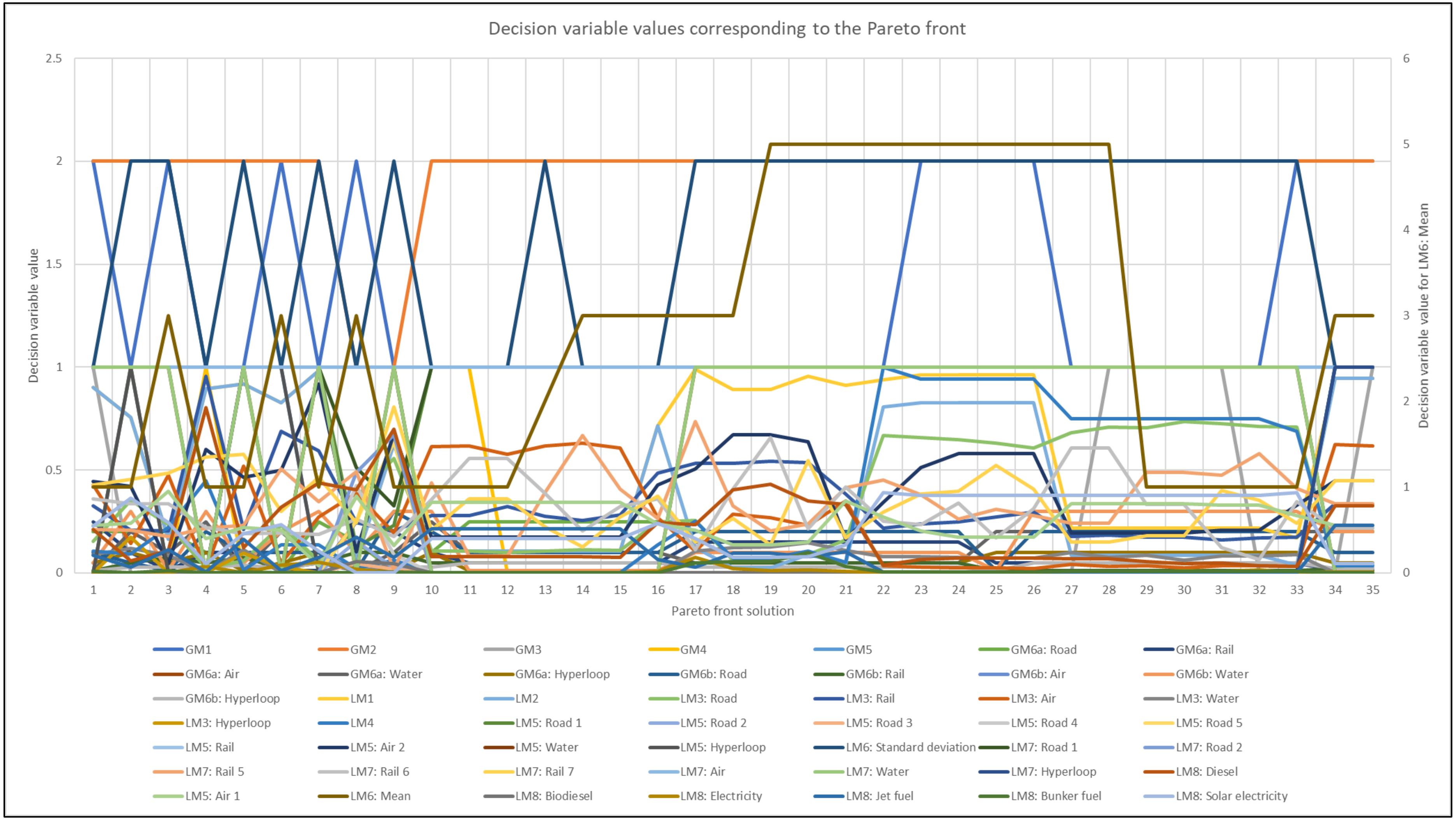


Figure 6.10 Decision variable combinations corresponding to the solutions on the Pareto front

6.1.3 Other validation techniques

A host of validation techniques exist in the literature. The modeller can opt to obtain stakeholder input on the scope and extent of validation techniques they require, in order to narrow down the scope of the validation process. Degenerate tests are examples of a validation technique. These tests model behaviour through the appropriate selection of values of the model's input and internal parameters (Sargent, 2011). For example, if all freight is allocated to a specific vehicle type, the tonne-kilometre values in the model should increase accordingly for that vehicle type.

Degenerate cases for a model are those values of input parameters which are at the extremes of the model's intended range of representation and degeneracy testing consists of checking that the model works for these extreme values of system and input parameters. Although extreme cases may not represent typical cases, degeneracy testing with extreme values can help the modeller to find bugs that would otherwise not have been discovered (Sargent, 2011). Numerous degenerate tests were performed during development of the FTEMT.

Face validity is another validation technique that can be applied to great effect. Here individuals that are knowledgeable about the system are asked whether the model and its behaviour is reasonable (Sargent, 2011). Several interviews with operations research experts, as well as transportation experts, have been conducted to confirm model validity throughout the course of this research.

Sensitivity analysis is a validation technique where values of the input and internal parameters of the model are systematically changed to determine the effect on the model's behaviour or output. The technique can be used both qualitatively (where only the directions of changes to the output matter) or quantitatively (where both the direction and magnitude of output changes matter) (Sargent, 2011). The purpose of a sensitivity analysis is to identify variables and parameters in the model that cause significant changes in the model's behaviour or output, so that care can be taken to ensure the accuracy of the values used for these parameters or variables. If a model is found not to be overly sensitive to the parameter values used, it is deemed robust. High robustness is a preferred quality for models where data availability and data reliability are low.

As an example of sensitivity analysis on the FTEMT, variations to the tax rate value used in decision variable GM3 were modelled. A hill-climb algorithm was applied to all the solutions in the initial archive. Each solution was modified in terms of GM3 for four different values of the tax rate used. The tax rates modelled were R60/t, R120/t, R240/t and R1200/t. None of the 52 perturbed solutions explored improved upon the initial archive, showing that not even a ten-fold increase in the value of this parameter substantially impacts the model and the model can be deemed insensitive to the tax rate set in GM3. This can serve as an indication to decision-makers that this freight energy management measure might not be the most promising measure to pursue.

A similar sensitivity analysis was done on the driver training efficiency improvement measure, GM4. Four different measure settings were applied to each solution in the initial archive in a hill-climb algorithm (Table 6.1). Again, none of these perturbations improved upon the Pareto frontier, indicating that the model is not highly sensitive to GM4.

Table 6.1 Sensitivity analysis measure settings for variable GM4

Mode	Setting 1	Setting 2	Setting 3	Setting 4
Road	0.5%	5%	10%	0%
Rail	1%	10%	20%	0%

The various combinations of a priori modelling parameters experimented with in Section 5.1.1 is another example of a sensitivity analysis performed on the case study model. Sensitivity analysis can be used to enhance the quality of the decision support provided, by taking uncertainties surrounding the real-world application of the model into account and exploring model robustness in terms of these uncertainties. This can be done in a similar vein to the sensitivity analysis examples mentioned. A real-world application of the FTEMT will yield additional opportunities to validate and calibrate the model, by comparing the results with actual system data, where applicable.

6.2 Case Study Model Results

Although all of the solutions on the Pareto front are equally good in theory (as per the definition of Pareto optimality), inspection of the objective function values shows that certain solutions outperform others in terms of the individual criteria. There is, thus, a 'best' solution in terms of each objective within the Pareto solution set. Table 6.2 provides a colour map of the objective function values for each solution in the Pareto front. The darker green in colour a value is marked, the better that value scores in terms of that objective. The different shades of red indicate unfavourable performance in terms of the objective, with the darkest red indicating the worst performance. The trade-off between the environmental and social objectives demonstrated in the plots of the Pareto front (Figure 6.6 and Figure 6.7) is evident in Table 6.2, as well, and the somewhat erratic, indifferent behaviour of the economic objective comes to the fore.

Speaking in terms of the environmental objective, Solution 33 is the best solution. Solution 27 performs the best in terms of the economic criteria and Solution 12 is preferred from a social impact perspective. Solution 7 is regarded as a 'balanced' solution – it fares relatively well over all three objectives.

Table 6.2 Colour map of the objective function values

Solution Number	Objective			Cluster Number
	Environment	Economy	Social	
33	-0.006520	0.534788	2.687522	1
24	0.000310	0.534831	3.006444	1
27	0.001192	-0.000014	2.584812	1
23	0.008166	0.534845	3.028315	1
29	0.008590	0.000002	2.869107	1
25	0.008752	0.534878	3.137683	1
31	0.009741	0.000016	2.915518	1
32	0.009974	0.000020	2.935814	1
26	0.010893	0.534855	3.132634	1
22	0.020242	0.000099	3.105588	1
28	0.028275	0.000006	3.213487	1
6	0.030885	0.998774	3.859157	1
2	0.039184	0.464628	3.262873	1
30	0.046254	0.000010	3.745020	1
4	0.061746	0.000202	6.872508	3
17	0.147478	0.000094	3.758952	1
7	0.186434	0.000154	8.568003	3
5	0.218534	0.464688	8.712863	3
1	0.235443	0.534112	9.705296	3
20	0.251931	0.000092	4.440524	1
3	0.283771	0.534183	11.256348	2
19	0.353157	0.000132	5.464728	1
18	0.390433	0.000100	5.808112	3
21	0.529099	0.000081	7.119609	3
9	0.541682	0.363710	10.944467	2
8	0.601058	1.412129	13.397177	2
16	0.613309	0.000152	8.508246	3
14	1.085752	0.000152	12.310579	2
15	1.087735	0.000150	12.384152	2
34	1.167531	1.000318	13.048972	2
35	1.168302	1.000214	13.071757	2
13	1.171022	0.000158	13.219448	2
10	1.210171	0.000157	13.619513	2
11	1.219979	0.000141	13.724390	2
12	1.222711	0.000128	13.872158	2

As the purpose of the FTEMT is to provide decision support on energy management strategies, it makes sense to look at the solution that performs the best in terms of overall energy demand in the network. The data shows that this value is highly correlated (correlation of 0.82) with the environmental objective, which makes sense, considering that performance in terms of the environmental objective is calculated from energy demand values. Solution 33 is, consequently, the best performing solution in terms of overall energy demand. The four best-in-class solutions are highlighted in blue in Figure 6.11 and Figure 6.12.

It is worth mentioning that the objective values themselves do not convey any meaning - they are the result of several normalisation iterations. These normalisation processes are performed after every model iteration, during which some of the solutions used to calculate the index values used are discarded. The negative objective function values result from these normalisation processes. Regardless, a relative comparison between the objective scores for each solution do convey meaning, enabling comparisons between the various solutions.

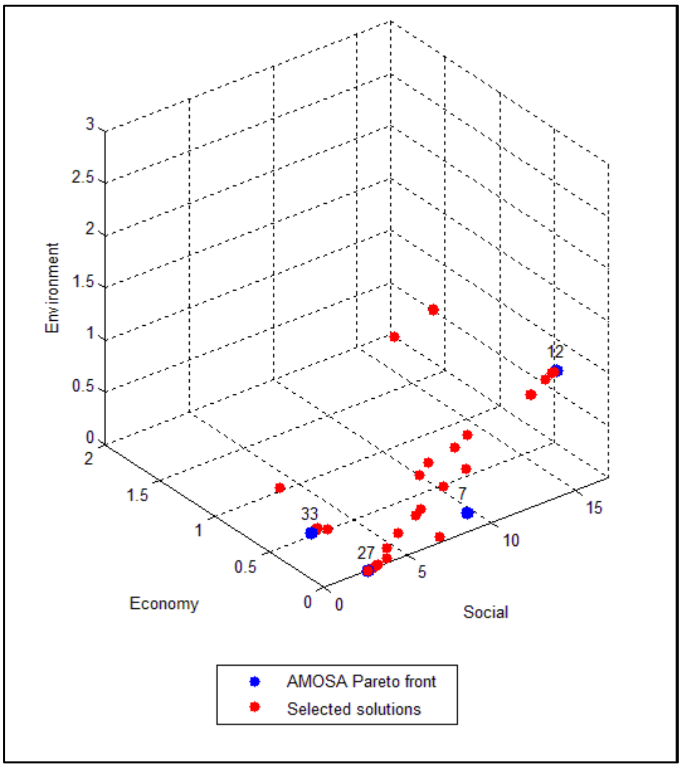


Figure 6.11 3D views of the selected solutions for further analysis

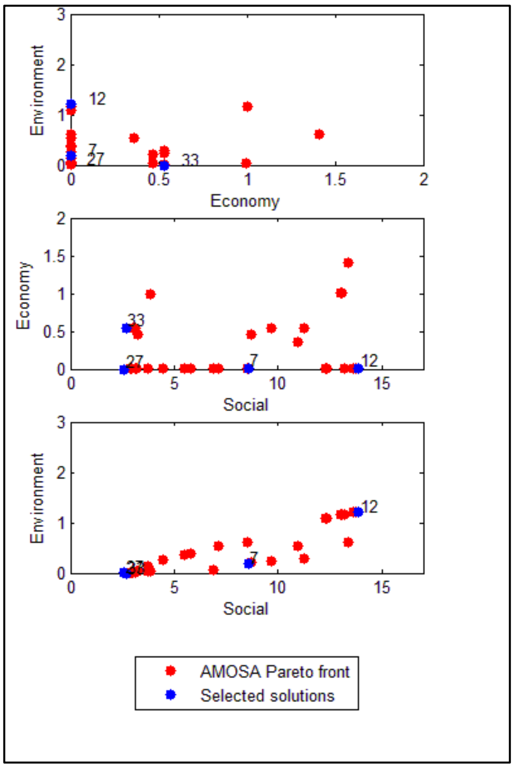


Figure 6.12 2D views of the selected solutions for further analysis

Mapping from objective space to design space, every solution represents a specific combination of energy management measures. It is not possible to isolate the impact of a specific measure when interrogating the composition of a solution, because the objective space scores of a solution is intrinsically linked to the simultaneous, combined impact of all measures. To determine the impact of a specific measure in a particular solution, a posterior sensitivity analysis on that solution is required.

Comparisons between solutions should, thus, be made considering the full combination of measures employed in each solution.

To demonstrate the information underpinning every solution in the objective space, the four 'best in class' solutions identified will be analysed in detail. These solutions represent the extreme cases in terms of individual objective performance and should provide context and a framework for the assessment of any intermediate solutions in the Pareto set.

Solution 33, the environmental best performer, adopts the network design which includes the SwaziLink rail development. This decision comes at quite a high cost and is mainly responsible for the solution's poor performance in terms of the economic objective. Only electric trucks are permitted in this solution. This, combined with the facts that 83% of trips in this solution are unimodal and the modal split heavily favours road freight (71%), leads solar electricity to be the main source of energy in this solution (94%). Solar electricity is the most efficient source of energy for freight transport and does not generate any direct CO_2 emissions. This explains the solution's great performance in terms of the environmental objective. Additionally, road transport has the second lowest jobs per tonne-kilometre ratio (specified in Section 3.3.3), explaining the poor social objective performance. Figure 6.13 displays the modal split and Figure 6.14 the energy split in Solution 33.

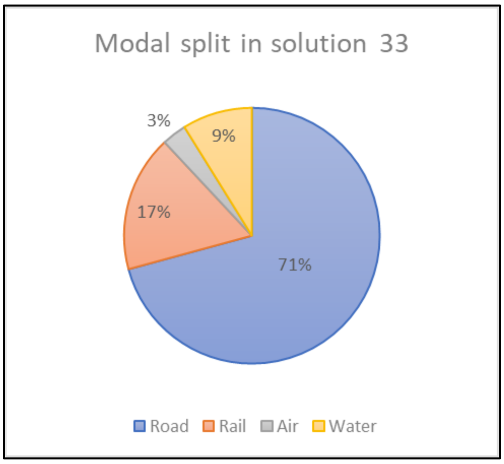


Figure 6.13 Modal split in the environmentally best performing solution (33)

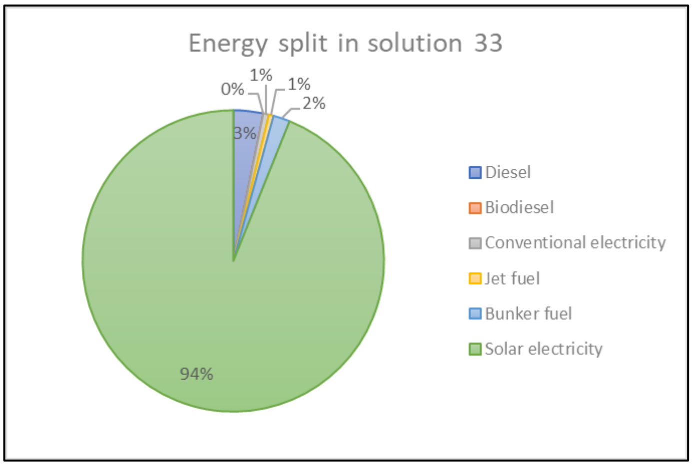


Figure 6.14 Energy split in the environmentally best performing solution (33)

Although the prevalence of road freight overloading is high in this solution, the tolerance for overloading of trucks is limited to 1%, which suggests that, environmentally speaking, heavier load allowances are not required to improve overall energy use here. Government level measures to improve overloading legislation enforcement or relaxing policy on load limits do not appear to be worth the effort in this situation. This notion is supported by the low mean value used for the vehicle loading regime decision variable – on average, vehicles are only loaded to 75% capacity before being dispatched. Efforts to get logistics operators to only operate fully laden trucks will not reap substantial environmental rewards when offset against its economic and social impacts. None of the other government level measures (implementing a carbon tax, launching driver training campaigns or introducing a hyperloop) are included in this solution. The conclusion that can be drawn from their omission is that the cost of their inclusion, in terms of the economic and social objectives, exceeds the environmental benefits they yield.

Surface freight captures 88% of demand in Solution 33, with rail transport at 17% of the modal split. Air transport is only used for 3% of all freight and water-based transport for the remainder. The network assignment for Solution 33 is shown in Figure 6.15. The thickness of the line segments corresponds to the tonne-kilometres travelled on that segment – higher tonne-kilometre values are indicated by thicker line symbols. A substantial number of road segments in the network (Figure 3.9) are not assigned any freight in this solution. In fact, Figure 6.15 shows that routing in the road network is done as directly as possible and that the network is, thus, not loaded uniformly. A few segments are used to transport virtually all the freight. Harrismith, Mooi River and Richard's Bay are examples of nodes where intermodal transfers are required.

Inspection of the rail network assignment in Figure 6.15 shows fairly extensive use of rail in the network. The electro-diesel locomotive (Class 38-000) is assigned the majority of rail freight (41%). The two types of diesel locomotives are used to transport the rest. Both the tolerance and prevalence of rail freight overloading is low. It might seem curious that freight is assigned to the railway segment between Richard's Bay and Golela, a seeming dead end. This can be ascribed to the routing algorithm used in the FTEMT where three routes are generated between every OD pair, when possible. To comply with this stipulation, indirect (and suboptimal) routes can be developed and assigned freight. A change to the routing algorithm used in the FTEMT will eliminate idiosyncrasies such as this. There is, thus, still some room for improvement for the model in terms of this solution, should resources allow greater exploitation in the search algorithm to play around with better route assignments.

The decision variables on vehicle split (for road, rail and water transport) and on propulsion system split (for road, air and water transport) do not convey any insights in this solution, because there is only one option to choose from for each of these decisions. Air freight favours the smaller aircraft over the larger one by 33%. Overloading on water-based transport is allowed, with 30% of vessels being overloaded by around 20%. Quite a high number of empty trips (42% of total tonne-kilometres) are generated in this assignment. Empty running shows some correlation to the expansiveness of the network assignment – the more nodes included in the network, the higher the potential for empty running becomes. Also, the greater diversity in terms of modal allocation, the higher the potential number of empty trips, as a greater variety of vehicles will have to be relocated.

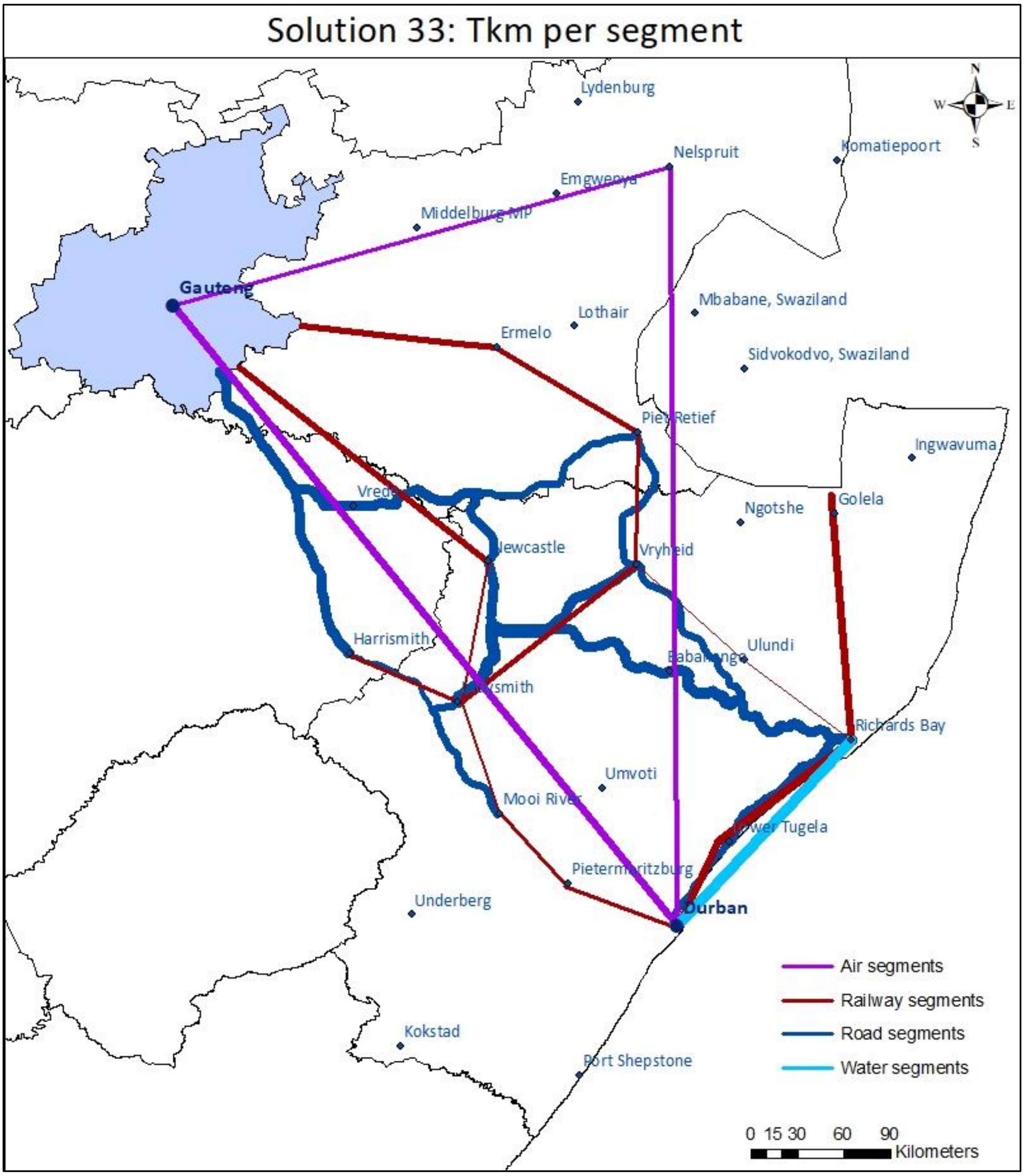


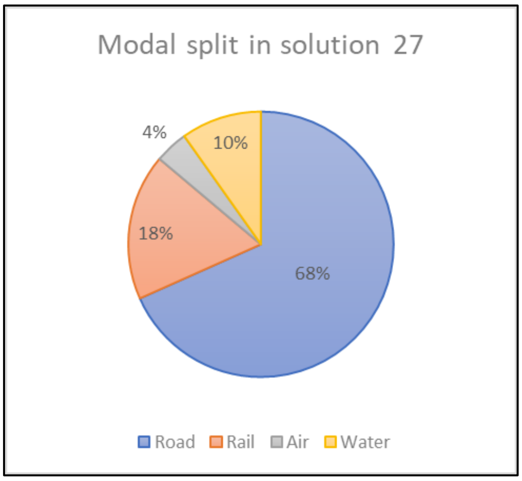
Figure 6.15 Network assignment in the environmentally best performing solution (33)

All in all, the logistics measures are seen to have the greatest influence on the environmental performance of the solution. The introduction and promotion of the use of freight modes that achieve excellent environmental impact scores appears to be the decision-maker's best freight energy management measure combination when environmental performance is the most important objective.

The only difference in government level energy management measures applied in the economic best performing solution (Solution 27) versus that in Solution 33, is that the SwaziLink railway is not included in this solution. This certainly accounts for the far better performance in terms of the economic objective. There are also slight differences in terms of the logistics measures. The modal split assigns 3% less demand to road freight and splits this evenly between the other three modes (Figure 6.16). This similar modal split and vehicle park selection yields a similar energy split to that of Solution 33 (Figure 6.17). The high prevalence of solar electricity in the energy supply mix accounts for the solution's good performance in terms of the environmental objective. The bulk of the rail freight (76%) is powered by diesel locomotives in this solution and the electro-diesel locomotive is only used as a diesel locomotive, accounting for the larger share of diesel and lack of conventional electricity in the energy mix. This causes the slightly worse environmental performance than that of Solution 33. Again, there are no decisions to be made on vehicle type or propulsion systems for the modes with only one viable option. The smaller aircraft is assigned even more air freight (81%) in this solution.

In terms of the network assignment (Figure 6.18), there is a higher incidence of intermodal trips, although the total percentage of trips (22%) remains low. The road network used is a bit more extensive than in Solution 33 and the rail network more concise. Overall, the network relies on a higher concentration of transport on a smaller number of segments. There is a corresponding (albeit slight) decrease in the number of empty tonne-kilometres travelled in this solution. This probably results from the very high mean vehicle load percentage of 95%.

The spurious road freight assignment on the segment connecting Ingwavuma to the network is the result of the network segment specification used in the data underlying the model. This data set specifies one segment for transport between Ingwavuma and Piet Retief and another segment connecting Richard's Bay to Ingwavuma. In retrospect, the segment should only have been specified as the link between Ingwavuma and the N2. With the current model specification, the model sends freight from Richard's Bay to Ingwavuma and from Ingwavuma to Piet Retief, when all of this freight should have been on the N2 only. This provides an example of how the results analysis can assist in weeding out model errors and inconsistencies, ultimately contributing to operational validation of the model.



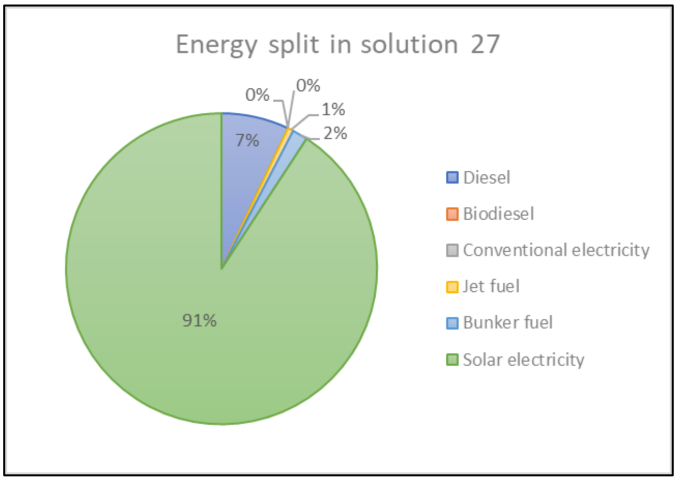


Figure 6.16 Modal split in the economically best performing solution (27)

Figure 6.17 Energy split in the economically best performing solution (27)

Solution 27's poor performance in terms of the social objective can be ascribed to the low modal share of air freight in the network. The good economic performance stems from the fact that there are no capital expenses or taxes applicable in this solution. The total spend on maintenance in this solution is the lowest of the four solutions in question. This suggests that decision-makers should avoid measures that impose additional costs on the system, such as capital expenditure or taxes. Measures aimed at reducing spend on fuel (by promoting transport utilising cheaper fuel sources) and maintenance (by promoting the use of modes that generate lower ESAL levels) are to be preferred. The vehicle park measure is very effective in reducing the total cost of the solution, because solar trucking incurs far lower fuel costs, compared to regular diesel trucks.

Solution 12, the best solution in terms of the social objective, has the same measure settings for the first five government level measures as Solution 27. The modal split in Solution 12 (Figure 6.19) is distinctly different, though. Air freight is assigned the greatest share of freight, followed by rail and road transport, respectively. No water-based transport is included. This modal split is the reason for the solution's excellent performance in terms of the social objective and poor performance in terms of the environmental objective. Figure 6.20 displays the corresponding energy split in Solution 12. All rail transport in this solution is propelled with diesel and the trucks with solar electricity. Fossil fuels account for 60% of the solution's energy supply.

The high level of air freight corresponds with low levels of intermodality (10%), because the air transport network directly connects the OD pair and no connections between network segments are required for this mode of transport. This also correlates to the low percentage of empty tonne-kilometres (22%). Relocation of only two types of aircraft (of which the smaller type is assigned 83% of demand) between three nodes does not incur a high number of empty trips. This solution uses an extensive road network in its network assignment and does not concentrate road or rail freight on main corridors only. This translates into more jobs required, as the total number of jobs is calculated on a per tonne-kilometre basis. Figure 6.21 presents the network assignment used in Solution 12.

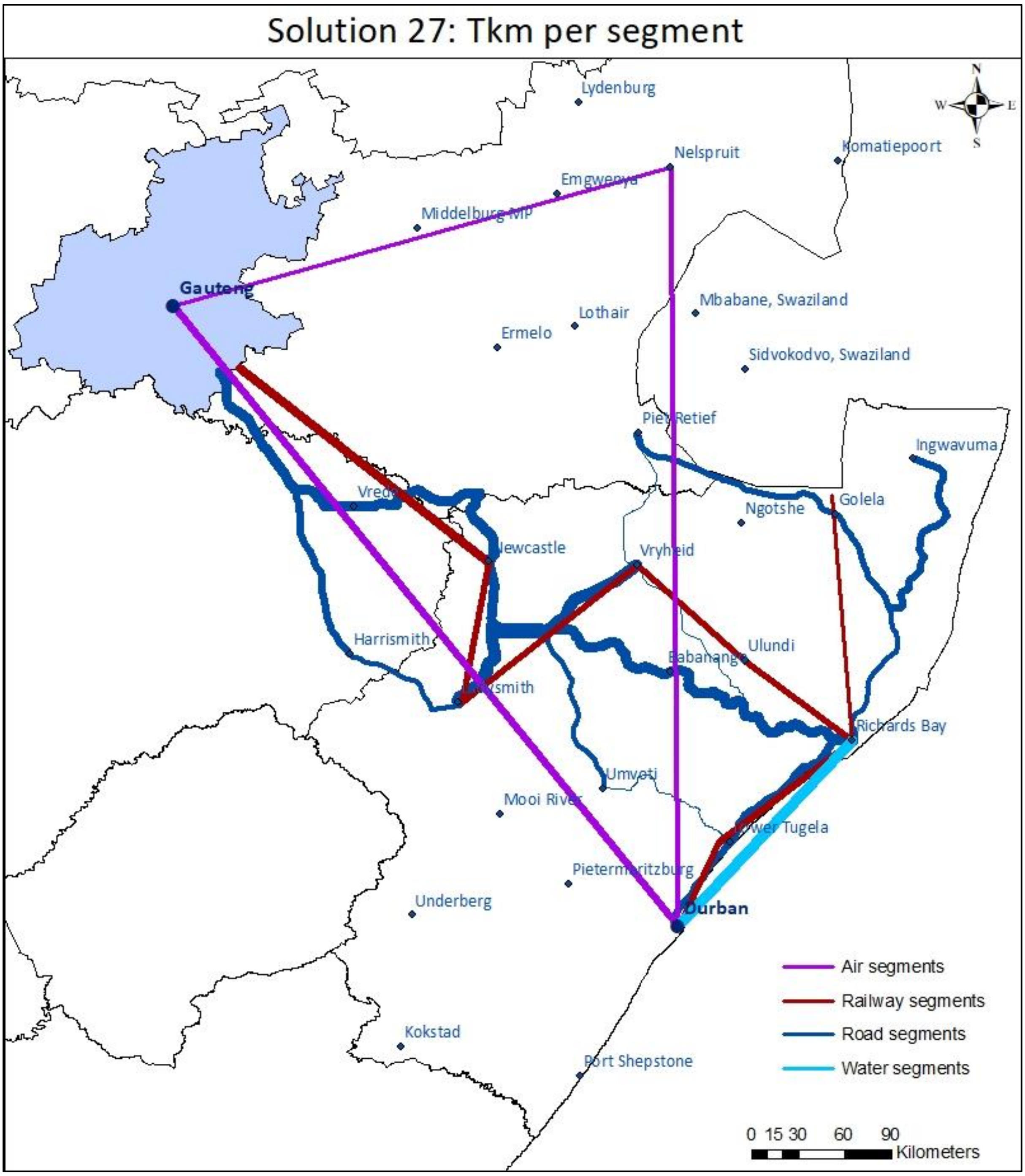
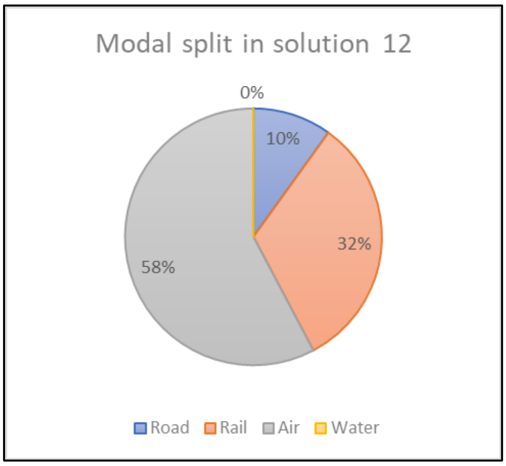


Figure 6.18 Network assignment in the economically best performing solution (27)



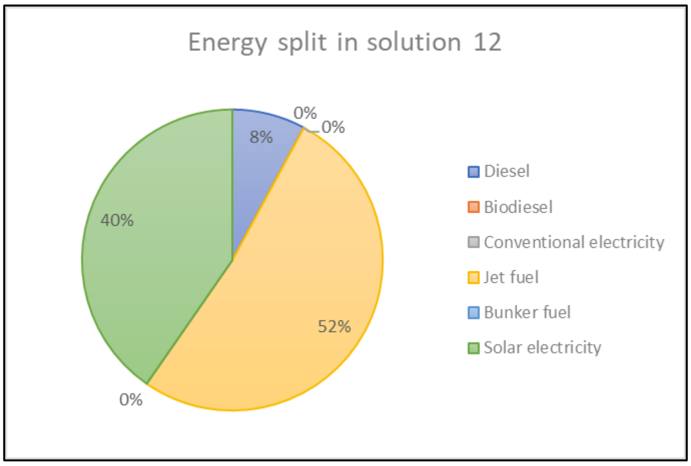


Figure 6.19 Modal split in the socially best performing solution (12)

Figure 6.20 Energy split in the socially best performing solution (12)

Vehicles are loaded up to 75% of capacity, in general, in this solution, whilst 10% of trucks are up to 25% over their load limits and 5% of rail wagons exceed their load limits by 5%. These values provide no clear indication of a preferred measure setting for the respective decision variables.

Solution 12 is a 'middle of the road' solution in terms of economic performance. The lack of capital expenditure and taxes boost the economic performance, coupled with the fact that jet fuel is one of the less expensive fuel sources. The maintenance cost associated with air freight is, however, quite high and the solution's ESAL values the highest of the four solutions being analysed. Decision-makers can infer that policy aimed at promoting the use of transportation modes with the highest associated job opportunities will yield the best results in terms of their social development goals.

Solution 7 fares reasonably well in terms of all three decision objectives at the same time. This solution uses the first network design and the pro-electric vehicle park. In contrast to the three solutions previously discussed, both the carbon tax and driver training measures are employed in this solution. The hyperloop is also not included here. Overloading tolerance is at a maximum for road freight and very restrictive for the other modes. Overloading prevalence is low for all modes, apart from water-based transport. Vehicles are typically loaded at around 75% of their capacity.

The modal split (Figure 6.22) reveals this solution to favour rail transport, followed by air freight, water-based freight and road freight, respectively. The high dependence on rail transport relates to 57% of the total energy demand (

Figure 6.23) - 35% of rail freight is moved with the electro-diesel locomotive and the majority with the diesel only locomotives. Only 25% of the energy in this solution is supplied by a clean energy source (solar). The rest is directly, and indirectly, dependent on fossil fuels. Despite this, the lower share of air transport enables this solution to perform better in terms of the environmental objective than Solution 12. Air freight does, however, still capture 27% of total demand, which corresponds with the solution's moderately good performance in terms of the social objective. The larger aircraft body is preferred by 91% in this solution.

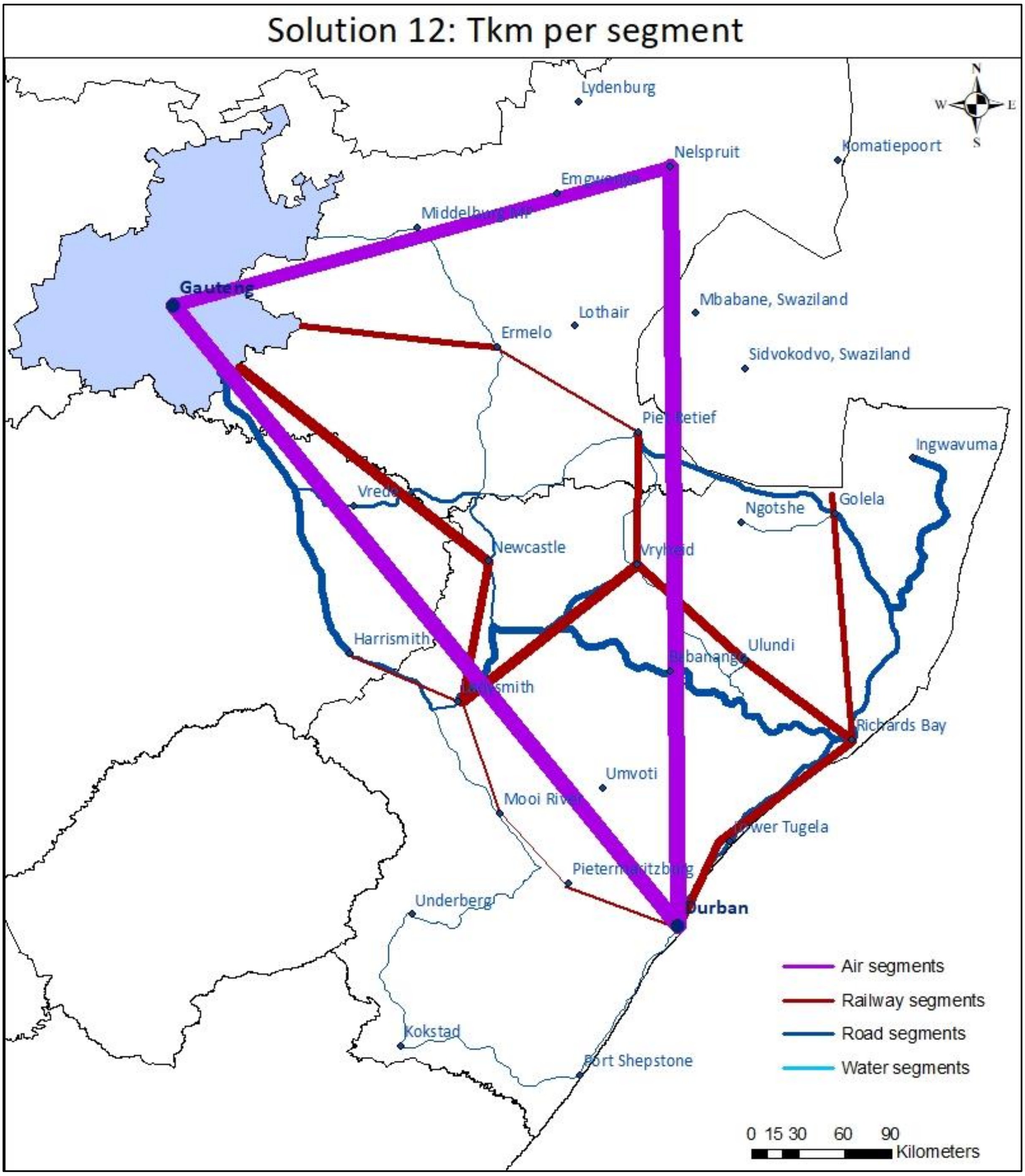
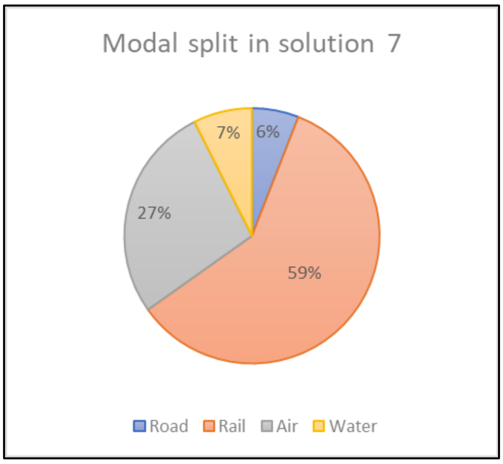


Figure 6.21 Network assignment in the socially best performing solution (12)



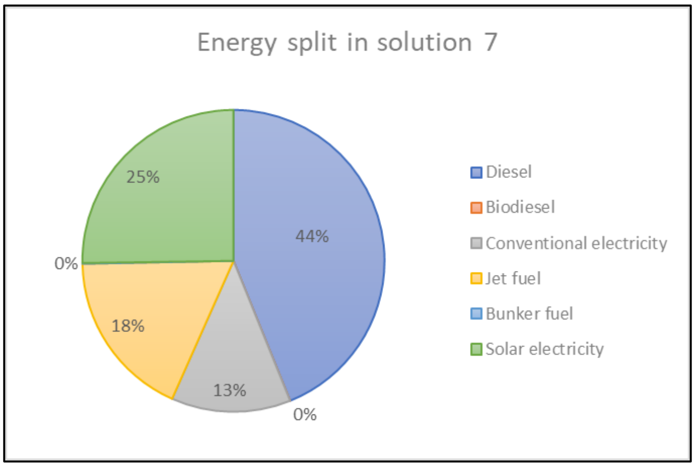


Figure 6.22 Modal split in the most balanced solution (7)

Figure 6.23 Energy split in the most balanced solution (7)

Network utilisation is fairly balanced in this solution, as a result of the more balanced modal split and high levels of intermodality (98%) requiring the use of more segments in the network. The network assignment is displayed in Figure 6.24. Empty running is at a maximum in this solution (49%). The exclusion of the SwaziLink and hyperloop solution keeps the solution's economic performance in check, although there is room for improvement in terms of this objective. Both the tax and driver training measures add to the total cost.

Decision-makers can deduce that a balanced modal split, combined with the avoidance of major capital-intensive measures, will yield a balanced solution in terms of all three objectives. Looking at the four solutions, two energy management measures stand out as the most influential in terms of the objective functions. These measures are vehicle park selection (GM2) and modal split (LM3). The solution with the lowest total tonne-kilometres is the worst environmental performer – solely due to the modal split used in this solution. It can be concluded that policy aimed at manipulating the type of transportation used in the network will be the most effective and should be pursued by decision-makers. This spans policy on the specification of mode (LM3 and GM5), vehicle type (GM2, LM5 and GM5), propulsion system (LM7) and energy sources (GM2 and LM8) to be used in the network. New, cleaner transport modes can, and should, be introduced, subject to this not inducing exorbitantly high capital expenditure outlays.

The analysis of these four extreme solutions demonstrates the operational validity of the FTEMT. The results are traceable, consistent and in line with expectations. Although the impact of individual measures cannot really be extracted from the solutions, per se, it is interesting to look at the cause and effect relationship of each measure, individually, over the entire solution set and to investigate whether any rules of thumb become apparent.

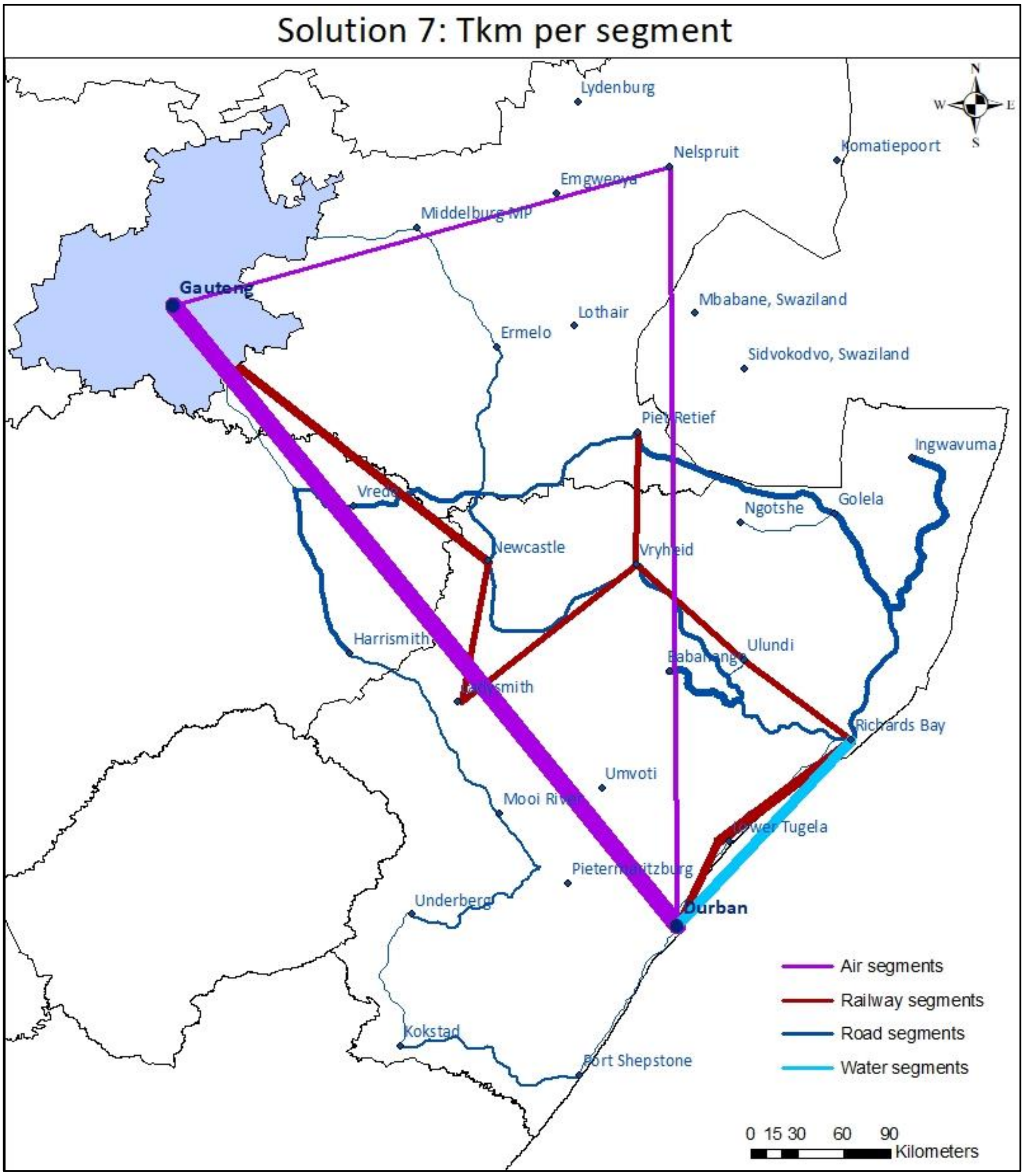


Figure 6.24 Network assignment in the most balanced solution (7)

This analysis starts with a look at correlations between the freight energy management measures and the problem objectives. Correlations are calculated using data from all the solutions in the Pareto set. As some of the measure values are qualitative and not quantitative, a positive or negative correlation indication is misleading and the directionality of the correlations becomes irrelevant. The absolute values of each correlation are shown in the correlation matrix in Table 6.3. Colour scales are used to indicate the relative correlation values of each pairing. Stronger positive correlations are shaded darker blue, while values remain white where no correlation is found. Correlations marked “N/A” represent measures that either have a constant value over all 35 Pareto optimal solutions, yielding a standard deviation of zero and a correlation calculation impossible, or measures that are not applicable to a certain mode (for example overloading is not considered a viable measure for air freight in the case study model).

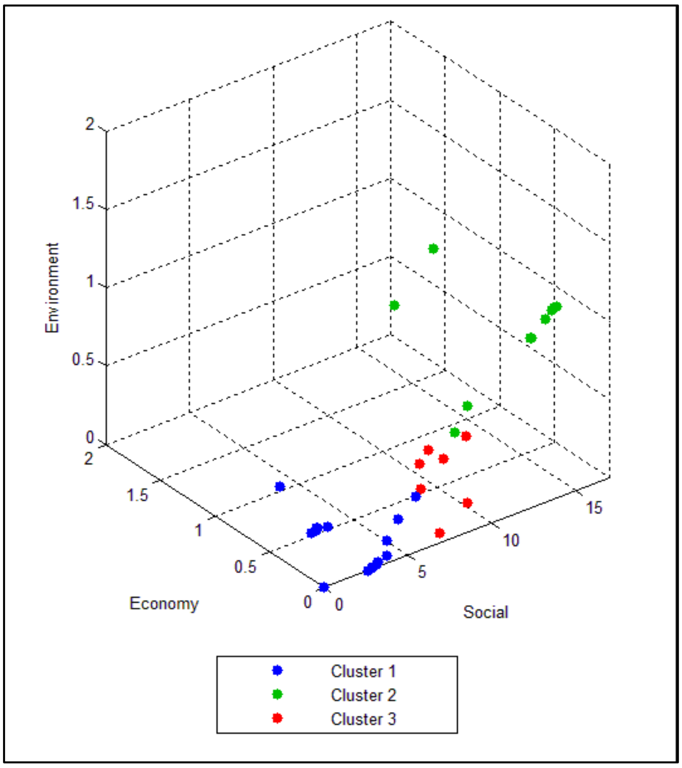
The modal split, LM3, and especially the modal allocation to road, air and water transportation, is highly correlated with a solution’s performance in terms of the environmental (and, thus, by default social) objective. The route allocation, LM4, and energy supply mix, LM8, also show high correlations in terms of these objectives. This substantiates what was gleaned from the analysis of the four extreme solutions. The network design, GM1, followed by the inclusion or exclusion of the hyperloop, GM5, are the only measures significantly correlated with the economic objective function. These are the two measures associated with high capital expenditures, hence these correlations were to be expected. Because correlations can be spurious and misleading, caution should be used to not read too much into the correlation values obtained, especially when these correlations are not substantiated by other analyses. For example, the high correlation of LM6 (standard deviation) is more a function of the measure having only one of two states, than of a true relationship between the measure setting and the objective function performance in a solution.

A correlation analysis between the various measures is shown in Table C1 in Appendix C. This analysis does not provide any new insights, but it does show that the model adheres to the interdependencies between measures, as the highest correlations are found between connected measures, serving as yet another form of operational validation.

K-means clustering is an algorithm used to find groups in data, with the number of groups represented by the variable *K* (Trevino, 2016). The algorithm works iteratively to assign each data point to one of the *K* groups, based on the features that are present. Data points are clustered based on feature similarity. This clustering algorithm was applied to the Pareto set (with k=3 to match the three sustainability objectives) in order to determine whether organic clusters reside within the front. Three distinct clusters could be identified. Table 6.2 displays the cluster allocation of each Pareto solution. The Pareto front (colour coded by cluster) is shown in Figure 6.25 and Figure 6.26. The clusters, though not terribly uniform, are spaced around the trade-off between the environmental and social objectives.

Table 6.3 Correlation matrix between decision variables and objectives

Decision Variable	Objective		
	Environment	Economy	Social
GM1	0.12	0.84	0.004
GM2	0.09	0.40	0.29
GM3	0.11	0.15	0.05
GM4	0.17	0.07	0.33
GM5	0.11	0.56	0.11
GM6a: Road	0.31	0.45	0.45
GM6a: Rail	0.30	0.09	0.49
GM6a: Air	N/A	N/A	N/A
GM6a: Water	0.42	0.018	0.42
GM6a: Hyperloop	0.06	0.54	0.04
GM6b: Road	0.35	0.30	0.37
GM6b: Rail	0.15	0.11	0.03
GM6b: Air	N/A	N/A	N/A
GM6b: Water	0.08	0.00	0.21
GM6b: Hyperloop	0.61	0.14	0.64
LM1	0.33	0.21	0.31
LM2	0.18	0.46	0.04
LM3: Road	0.64	0.01	0.69
LM3: Rail	0.02	0.08	0.02
LM3: Air	0.91	0.09	0.92
LM3: Water	0.68	0.22	0.67
LM3: Hyperloop	0.16	0.19	0.12
LM4	0.71	0.07	0.77
LM5: Road 1	0.09	0.42	0.29
LM5: Road 2	0.08	0.52	0.27
LM5: Road 3	0.09	0.50	0.29
LM5: Road 4	0.09	0.52	0.28
LM5: Road 5	0.08	0.23	0.23
LM5: Rail	N/A	N/A	N/A
LM5: Air 1	0.31	0.09	0.27
LM5: Air 2	0.31	0.09	0.27
LM5: Water	0.77	0.19	0.73
LM5: Hyperloop	0.11	0.56	0.11
LM6: Mean	0.20	0.09	0.33
LM6: Standard deviation	0.65	0.27	0.68
LM7: Road 1	0.09	0.34	0.27
LM7: Road 2	0.09	0.34	0.27
LM7: Rail 5	0.10	0.03	0.21
LM7: Rail 6	0.19	0.28	0.09
LM7: Rail 7	0.07	0.29	0.13
LM7: Air	N/A	N/A	N/A
LM7: Water	0.77	0.19	0.73
LM7: Hyperloop	0.42	0.48	0.34
LM8: Diesel	0.06	0.14	0.21
LM8: Biodiesel	0.09	0.44	0.29
LM8: Electricity	0.25	0.04	0.19
LM8: Jet fuel	0.94	0.12	0.93
LM8: Bunker fuel	0.17	0.27	0.27
LM8: Solar electricity	0.60	0.15	0.69



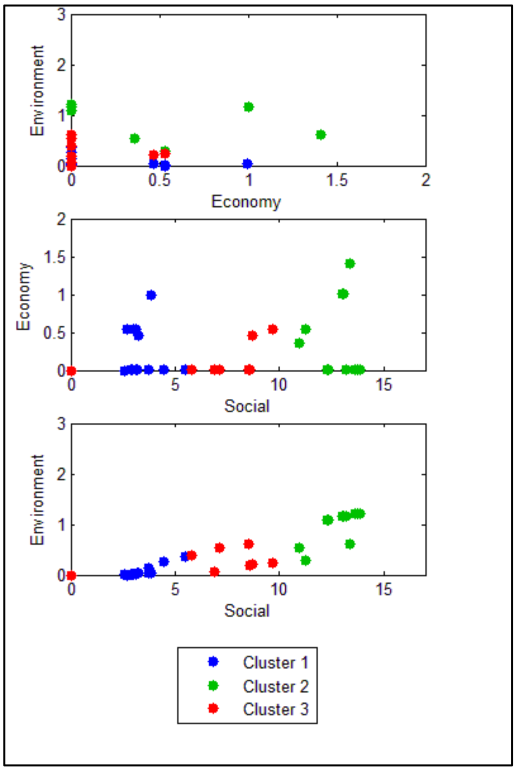


Figure 6.25 3D view of the clusters in the Pareto front

Figure 6.26 2D views of the clusters in the Pareto front

Solutions 33 and 27 belong to cluster one, Solution 12 to cluster two and Solution 7 to cluster three. The solutions can be seen as representatives for each cluster, as cluster one mainly corresponds with solutions that fare well in terms of environmental criteria and poorly on social criteria. The performance in terms of economic criteria in this cluster is split fairly evenly between positive and negative values. Cluster two contains the best solutions in terms of the social objective. These solutions typically fare poorly in terms of the environmental criteria and are fairly neutral in terms of economic impact. Cluster three is a mixed bag where solutions do not perform exceedingly well, nor poorly, in terms of any of the three criteria. Instead, some solutions are slightly positive in terms of all three objectives. Solution seven is an example of such a solution. The majority of solutions in the Pareto set (17) belong to cluster one. Cluster two contains 11 solutions and there are only 7 balanced solutions.

Overall, there is a preference towards the first network configuration with 68% of solutions in the Pareto set employing this option (for decision variable GM1). Almost half of the 51 solutions explored but discarded by the AMOSA algorithm opted to include the second network design. This measure certainly appears to impact whether a solution will be competitive or not.

Solutions in the Pareto set clearly favour the second vehicle park (which is pro electric trucks) with only two out of thirty-five solutions adopting the first vehicle park (GM2). This provides a strong signal to decision-makers to pay attention to this energy management measure. It should, however, be mentioned that this variable was not greatly explored in the AMOSA algorithm and a sensitivity analysis around this measure might provide greater confidence in this finding. Looking at the results from the AMOSA run that explored the greatest number of solutions (parameter configuration seven comprised 124 perturbations), however, it is seen that none of the 28 solutions that included the first vehicle park were non-dominant and Pareto optimal. Considering the dramatic impact that the use of solar powered electric trucks can have in the case study model configuration, this measure is deemed critical for inclusion in a freight transport energy management strategy.

Some 74% of Pareto optimal solutions did not include a carbon tax (GM3) and 80% did not opt for driver training (GM4). The inclusion of these measures in a freight energy management strategy does not seem likely. The hyperloop (GM5) formed part of the network in only five Pareto optimal solutions (Solutions 2, 5, 6, 34 and 35), none of which are part of the best-in-class solutions. Building a hyperloop is a very expensive option (the inclusion of the hyperloop in the network is strongly correlated to a negative economic impact in the solutions, as can be seen in Table 6.2) and the mitigating benefits in terms of the other objectives does not seem to outweigh the significant economic impact in this case. The amount of freight assigned to the hyperloop when it is included in a solution is not substantial enough to reap large environmental benefits. In fact, it is the modal split values in terms of air freight in these five solutions that render them part of the Pareto set, not the inclusion of the hyperloop. This measure does not appear to be a worthwhile inclusion in a freight energy management strategy.

The results on overloading (GM6) does not provide a clear signal, although there is a slight bias toward higher tolerance and prevalence values, in general. The cause and effect impact of this measure is not very strong. Figure 6.27 displays the values of decision variables LM1 (intermodal split) and LM2 (intramodal) split for the Pareto set. The values displayed represent the percentage of all demand allocated to intermodal or intramodal transport in each solution. The remaining freight is allocated to unimodal transport, by default. Solutions are grouped per cluster in Figure 6.27. There is high variability and no clear preference value for these decision variables across the entire solution set.

Some patterns do, however, emerge per cluster, where the first cluster contains a mixture of unimodal and intermodal dominant solutions, cluster two strongly relies on unimodal transport and cluster three on intermodal transport. Cluster two contains the socially strong performers, which correlates to a high use of air transport. Because the network segments used for air transportation directly connects to the origin and destination in the case study model, all freight bound for air transport will only make use of unimodal trips. This corresponds with the findings based on Figure 6.27. Moreover, the balanced solution considered representative of cluster three (Solution 7) illustrated that a balanced modal split yield balanced objective function impacts. It makes sense that a balanced modal split will correlate highly with intermodal trips. The decision-maker's preference in terms of which objectives to prioritise can, thus, influence whether policies encouraging intermodal freight should be included in a freight energy management strategy, or not.

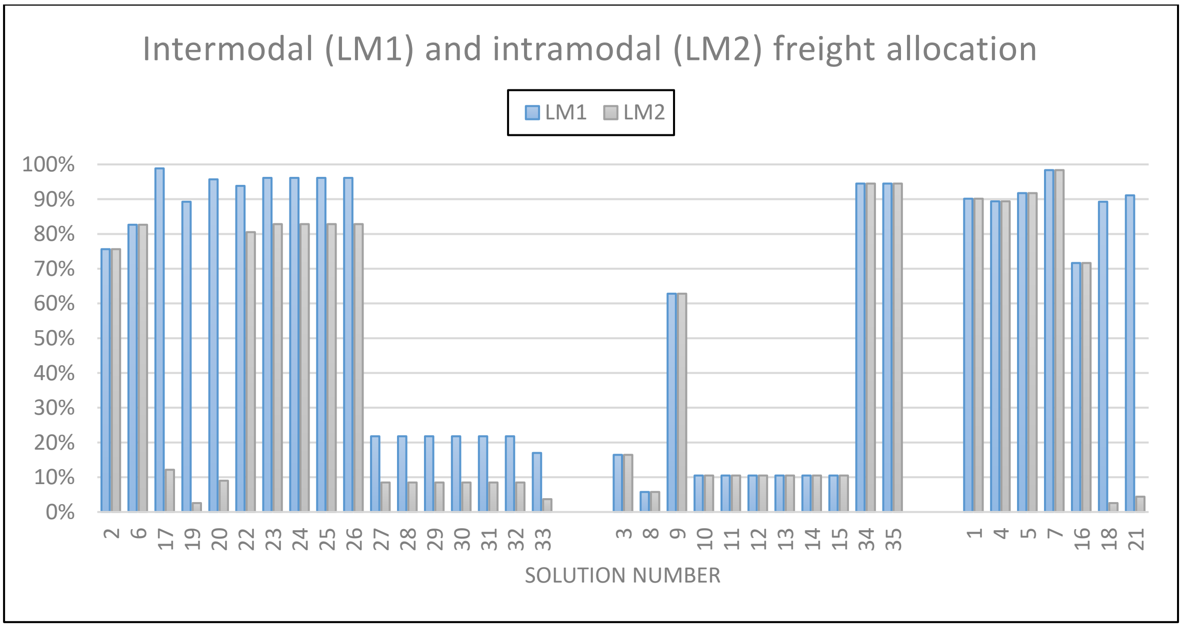


Figure 6.27 Splits for intermodal and intramodal freight in the Pareto set

The modal split (LM3) for each solution in the Pareto set is shown in Figure 6.28. Solutions are, again, grouped per cluster. The first cluster, which is the best cluster from an environmental perspective, strongly favours surface freight, with a preference towards road freight. In these solutions, where surface freight dominates, virtually no demand is allocated to air freight. This, in part, is the reason for the good environmental performance of these solutions. The fact that road freight is powered by solar electricity in this cluster seals the deal. Solutions in the second cluster prefer air freight over road freight, as air freight has the highest ratio of jobs per unit of transport of all modes (Section 3.3.3). Air freight is, however, a poor performer environmentally speaking. There is no water-based freight in most of these solutions; water-based freight is the transport mode with the lowest ratio of jobs per unit of transport. Cluster three contains the most balanced modal split profiles, with a weak preference for rail freight. Modal split is proven to be highly influential in terms of a solution's objective function performance. All freight energy management strategies should be developed with a keen focus on the effective modal split that policy supports.

While it is unorthodox and unexpected that the model will suggest air freight as the preferred method of freight transport for processed foods in some of the optimal solutions, interrogation of the underlying model construction does explain the model outputs. This result validates that changes to the measure settings for LM3 affect the model as can be expected (given the formulation of the objective function assessment criteria), though perhaps not as intended by the stakeholders. A result like this in a real-world application would flag that there are missing components in terms of calculating the true impact of air transportation. Stakeholder input could then be requested at this point, to review the air freight impact formulae and to suggest improvements in the model specification. Model development is an iterative process and experimentation with the computerised model based on an analysis of the results produced forms part of the standard modelling process (as depicted by Sargent (2011) in Figure 6.1).

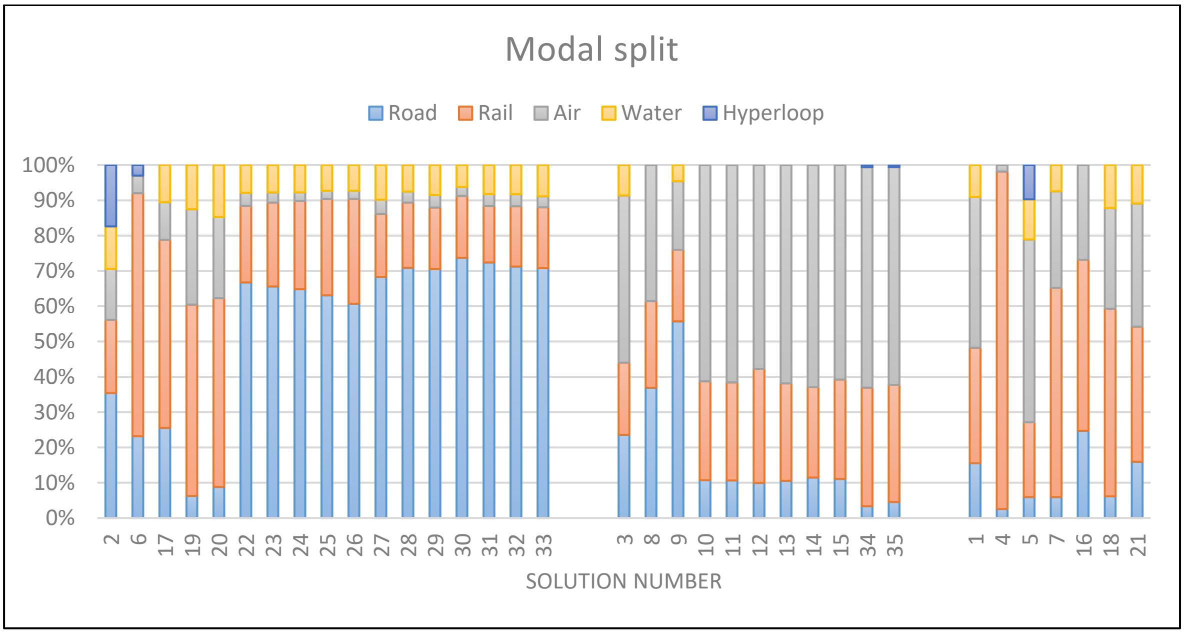


Figure 6.28 Modal split of the solutions in the Pareto set

To summarise the impacts of the route split decisions in LM4 over all Pareto solutions, the average load per segment in the network was calculated and a standard deviation per segment determined. This standard deviation metric was normalised on a scale of zero to one for each solution. A high standard deviation implies that certain segments in the network are heavily utilised, while others have been assigned virtually no traffic. A low standard deviation corresponds to a balanced route assignment over all segments in the network. A histogram of the values for LM4 over the Pareto set is provided in Figure 6.29. The vast majority of solutions (20 out of 35) have a very low standard deviation in segment load, implying equal utilisation of the network. The second largest grouping of solutions (12 out of 35), in turn, have very high standard deviations. Looking at the clusters, all of the solutions with a standard deviation above the 60th percentile belong to cluster one. The expectation is that a few route segments are loaded disproportionally heavily, whilst others are not utilised at all in these solutions. Cluster two has only one solution with a standard deviation above the 20th percentile; route splits here are levelled out in order to include the highest level of tonne-kilometres, positively impacting on the number of jobs required. Cluster three contains predominantly low values for LM4. Corridor bound surface freight seems to correspond well with good environmental performance. Freight route consolidation and policies that foster it is something that decision-makers should consider if good environmental performance is a priority.

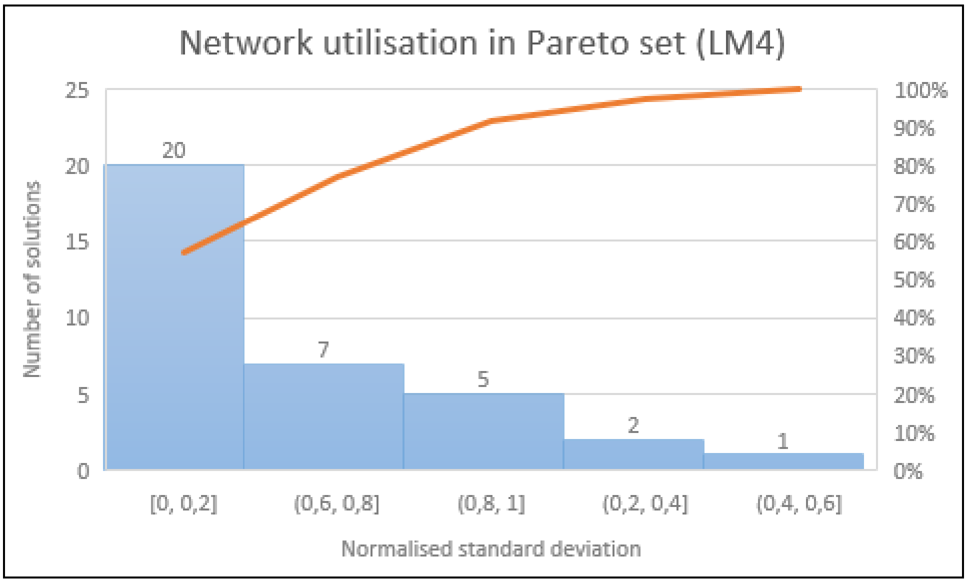


Figure 6.29 Histogram of the network utilisation scores for LM4 over the Pareto set

The two solutions that opted for vehicle park one (Solutions 8 and 9) both reside in cluster two and are some of the best performers in terms of the social objective, but fare poorly in terms of economic impact. These solutions do not perform well in terms of the environmental criteria, either. The vehicular assignments for these two solutions are distinctly different, evident in Figure 6.30. The rest of the solutions all have only one road vehicle type to assign all demand to. There is also no vehicle assignment decision made for rail transport, as there is only one wagon type compatible with transporting processed foods (Section 3.1.3). Locomotives are assigned by the propulsion assignment decision variable (LM7). Figure 6.31 shows the various aircraft assignments in the solution set and per cluster. There is no significant pattern emerging, although the solutions in cluster two tend to utilise the smaller aircraft, in general. Because both cabotage and the hyperloop use only one vehicle type, no vehicle assignment decisions are made for these modes, per se. LM5 is not a strong indicator of solution performance, on the whole. There is not enough information or evidence to suggest that policy should be aimed at promoting the use of particular vehicle types in the network.

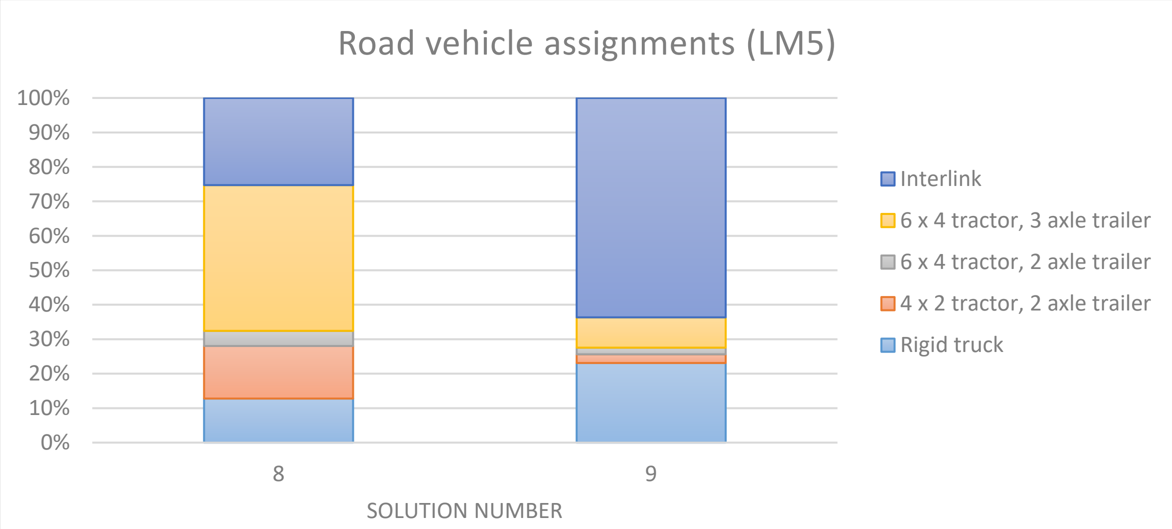


Figure 6.30 Road vehicle assignments in Solutions 8 and 9 of the Pareto set

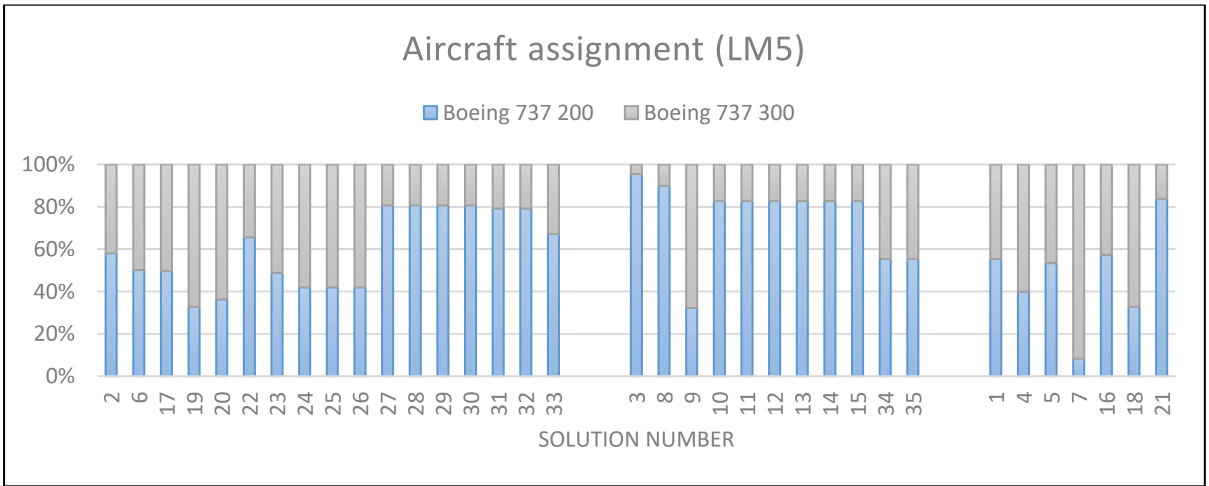


Figure 6.31 Aircraft assignment in the Pareto solutions (LM5)

The vehicle loading regimes per cluster shown in Figure 6.32 appear to provide some insight – cluster one contains the highest number of solutions that applied the highest capacity utilisation vehicle loading regimes possible. This can be translated into good environmental performance, in general, by eliminating unnecessary trips. The socially proficient solutions in cluster two favour the lowest capacity utilisation loading regimes, as this translates to more tonne-kilometres and, hence, higher levels of employment. Cluster three remains a mixed bag of loading regime settings.

The propulsion system split (LM7) for road transport is only relevant for the two solutions where vehicle park one is in effect. Solution eight has a 51% allocation to conventional internal combustion engines and 49% to biodiesel compatible trucks. The split for Solution nine is 33% versus 67%. There is not enough information to provide a strong signal about preference for conventional road transport propulsion systems. The case study model assigned rail transport to the three locomotives that can travel on any part of the rail network and not only on electrified tracks. Looking at the assignments per cluster (Figure 6.33) no clear preference for a particular locomotive emerges. Air freight, water-based freight and the hyperloop all rely on one propulsion system type; no further disaggregation is possible at this level. Policies steering freight operators towards the utilisation of certain propulsion systems do not seem necessary at this stage.

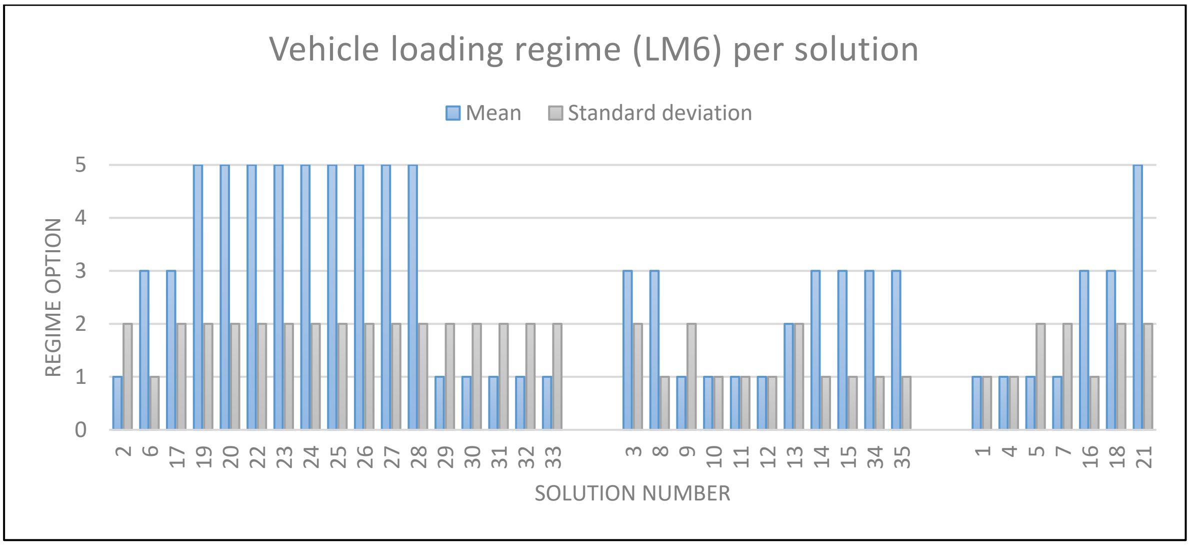


Figure 6.32 Vehicle loading regime (LM6) applied per solution in the Pareto set

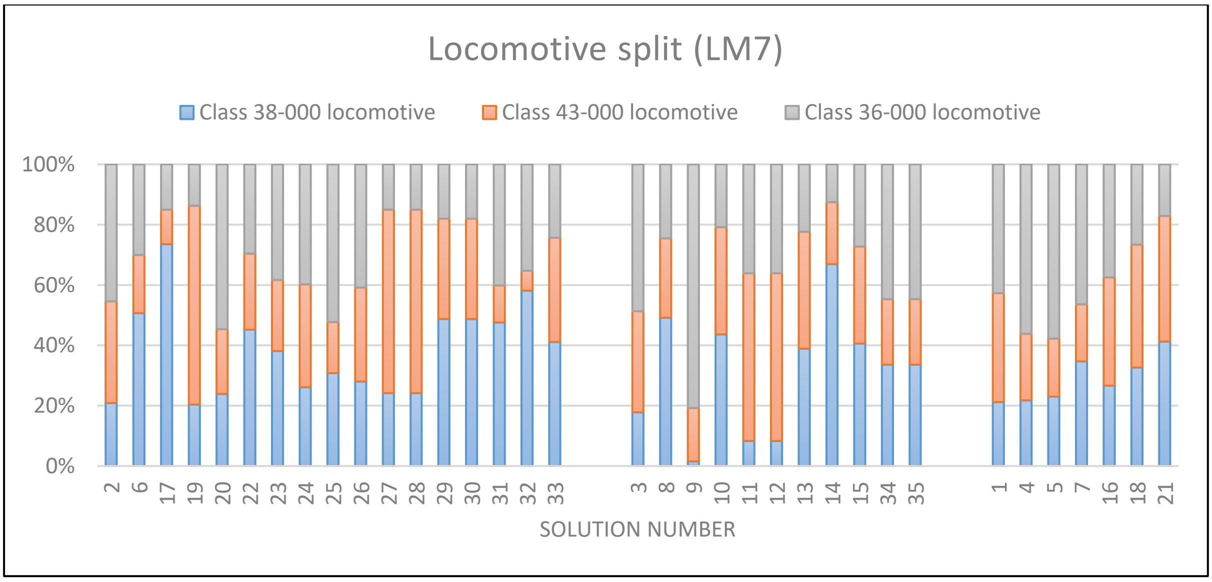


Figure 6.33 Locomotive assignment (LM7) per solution in the Pareto set

Figure 6.34 displays the effective energy splits resulting from the cumulative impact of all decisions made for each solution in the Pareto set. The splits are quite distinctive per cluster. In cluster one, solar electricity is the main energy source used. This corresponds to the good environmental performance of the cluster, as solar electricity is a renewable, cleaner and more efficient energy source than conventional fossil fuels. In cluster two, the energy supply mix is split between solar electricity and jet fuel, due to the high percentage of air freight assigned in LM3 in these solutions. The most balanced supply mixes are found in cluster three, corresponding to the cluster's balanced impacts over all three objectives. Interestingly, in the two solutions where road transport is non-electrified, biodiesel does power some of the trucks, though the vast majority of energy demand is fossil-based. It is evident that policy promoting the use of renewable energy will reap great environmental rewards for decision-makers.

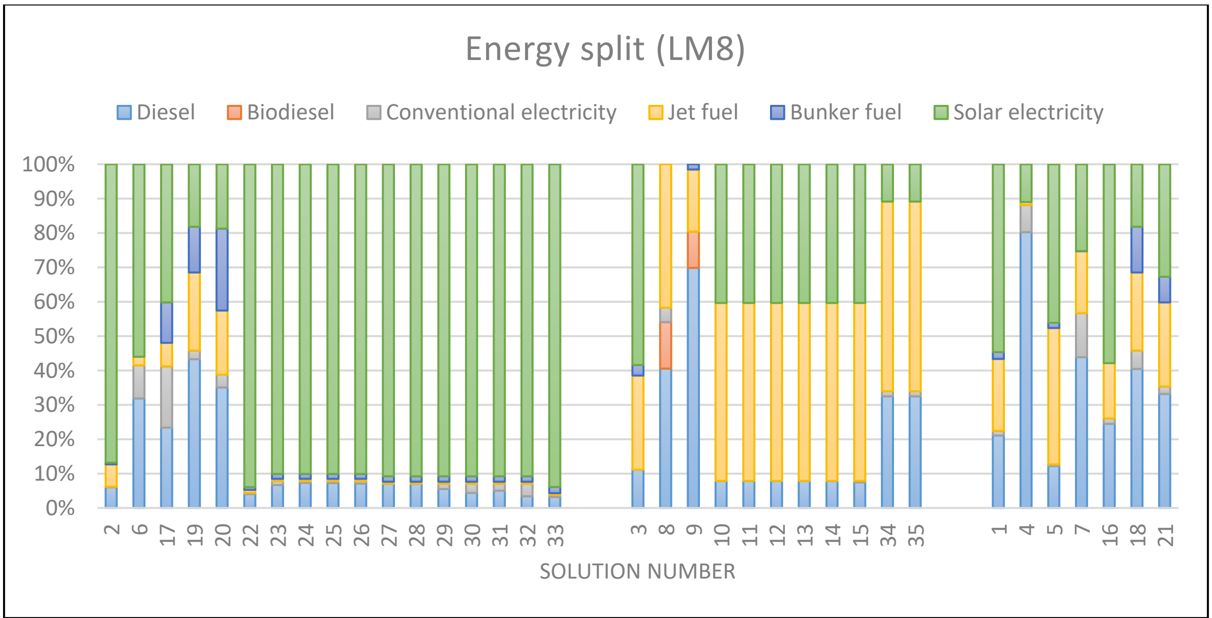


Figure 6.34 Energy split (LM8) per solution in the Pareto set

A table (Table D1) summarising the key findings per decision variable can be found in Appendix D. All the decision variable values for each solution in the Pareto set can be found in Table E1 in Appendix E. From the analysis it is clear that measure settings should be in harmony to achieve the desired objectives. It would not make sense to include electric trucks in a solution without assigning any freight to road transport, if good environmental performance is the goal, for example. It would, similarly, be self-defeating to favour corridor-bound surface freight when job creation is a primary concern in the case study network. This proves that measures should not be modelled and assessed in isolation, but rather as packages, as suggested in the problem statement in Section 1.2.

The results analysis presented here demonstrates the FTEMT's ability to generate measure combinations that do not contradict each other, but are aligned with each other to achieve good performance in terms of a common goal. The FTEMT is shown to produce vastly different combinations excelling at different goals, but they are all Pareto optimal and, hence, worth consideration. Decision-makers are presented with an array of internally consistent solution alternatives and it is their task to cherry pick the solution to be implemented from this point onwards.

It is acknowledged that the case study problem formulation and objective function assessment criteria used in this demonstration model are very basic, but this is preferred as the case study is only meant to showcase the functioning of the FTEMT and to serve as a foundation for validation of the tool. A highly complex problem formulation would not be as easy to validate, verify and explain. Now that the tool has been proven to perform its intended function in a reliable and acceptable manner, it can be used in real-world applications with confidence. The problem formulation can be expanded to include more elaborate, complex and realistic formulae and can be trusted to produce internally consistent results.

A second commentary on the results analysis is that the results shown and conclusions drawn in this section are only relevant for the case study model formulation; general rules of thumb for freight energy management should not be abstracted from the results assessment presented in this chapter without caution. However, should the model specification in a real-world application of the FTEMT satisfy stakeholders in terms of accuracy and scope, an analysis similar to the one presented here will yield conclusions that can be abstracted into rules of thumb and provide decision support on the formulation of freight energy management strategies relevant to the stakeholders' problem formulation.

Finally, it should be mentioned that, although the analysis of the model outputs presented here provide a lot of insight and information, there are many more ways of dissecting and interrogating the data, depending on the requirements and interests of the decision-makers. The analysis can be tailored to the real decision context. Only a sampling of possible analyses has been presented in this chapter.

6.3 Solution Selection

Once confidence in the validity of the model outputs is high, a suitable alternative will need to be selected out of the options generated, i.e. a decision needs to be made on which solution to implement. The solutions proposed in the final Pareto set are all distinctly different, even though they are Pareto optimal. Additional decision criteria need to be applied in order to determine which solution is the best fit for the decision-maker in question. This is where external influences on the model, such as political agendas and mandates, come into play. Decision-makers in first world countries with strong economies are likely to be interested in the environmental performance as a main priority, whereas in developing countries, where social inequalities abound (such as in South Africa), the political motivation to prioritise job creation above all other objectives might influence decision-making. Solutions in the Pareto set all present a trade-off in terms of the objectives to decision-makers, who effectively need to determine what they are willing to sacrifice in order to realise the particular gain that a solution offers, in terms of their most prized objectives.

When there are multiple optimal solutions to choose from, stakeholder involvement is pivotal and the use of additional decision tools, such as multi-criteria decision-making, is encouraged. Taha (2003) suggests that intangible (unquantifiable) factors must be accounted for, before a final decision can be reached. May *et al.* (2005) corroborate these sentiments, stating that model-based analysis needs to be used as a contribution to strategy formulation, rather than being seen as the whole process. An additional descriptive decision-making procedure to select the preferred solution for implementation is required, although this lies beyond the scope of the research presented in this dissertation. A simple example of such additional decision criteria would be to apply a stakeholder specified weighting coefficient to each solution in the Pareto set and to score and rank the solutions based on this new, combined objective function. The best solution will then be the solution selected for implementation. This is a very rudimentary approach, with a number of flaws, although it will identify one solution as the best. There is an entire field of research devoted to multi-criteria decision-making approaches which can be consulted to find a suitable method for selecting a solution based on the problem context in a real-world application. A good reference is a book titled Multiple Criteria Decision Analysis, State of the Art Surveys (Greco *et al.*, 2016) published by Springer.

Decision-makers concerned about the risk of making a decision that requires long term investments of substantial amounts might require the modellers to investigate the impact of uncertainty on the results produced by the FTEMT. Polasky *et al.* (2011) regard an approach to decision-making under uncertainty to be of value if it helps clarify the effect that alternative decisions have on the probable desirability of outcomes in terms of stated objectives. Put differently – how robust are the proposed solutions to external changes that occur beyond the system boundaries defined in the model. Sensitivity analysis on certain assumptions or parameters in the model identified by decision-makers for interrogation can be used to provide an answer to these questions. These answers can also inform on which solution is preferred if the most robust solution is sought by decision-makers.

Once a decision has been made, the final stage of the operations research process (the post-decision stage) takes effect. This stage consists of three steps: step eight – development of a decision support system, step nine – development of an implementation strategy and implementation of the solution chosen in step seven and step ten – monitoring of the implemented solution (refer to Appendix B). As mentioned in Section 1.7, these steps fall beyond the scope of this research. It is, however, worth mentioning that the selected solution will, typically, be subjected to a tactical level analysis during the development of an implementation strategy. The FTEMT solution indicates what the network assignment that decision-makers are aiming for looks like, but a tactical level analysis of what will be required to make this a reality might also inform solution selection – some solutions might be more realistically achievable than others, given the resource constraints governing any decisions made.

6.4 Chapter Summary

The purpose of this chapter was to validate the FTEMT through an analysis of the outputs developed by the tool and to showcase the decision support developed. The tool is found to be operationally valid, as it successfully achieves its stated objectives (the model finds a Pareto set of solutions close to the true efficient frontier through the exploration of different energy management measure combinations). The exposition of the results, presented in Section 6.2, illustrates the insights and information serving as decision support that becomes available to decision-makers when the FTEMT is used. Though it cannot be proven that the model finds the exact optimal answer, the true Pareto front, the answers developed are of acceptable accuracy to aid decision-making with confidence. The FTEMT explores the decision space and reduces the number of decision alternatives that decision-makers need to consider to a manageable number of solutions, all of which represent harmonic measure combinations, geared toward optimal performance in terms of the entire spectrum of the problem objectives. These solutions are developed taking all the complexity issues described in Section 1.2 into account. Decision-makers can, thus, have confidence that the adoption of any one of these solutions proposed by the FTEMT will be a responsible and sound decision.

A number of research questions are answered in this chapter. Question 3.2 (are some solutions better or worse than others) is answered in Section 6.1.1. This section also addresses questions 3.3 (is there a Pareto frontier and a trade-off between solutions), 3.5 (is the search space sufficiently explored) and 3.6 (does the model converge). The results analysis in Section 6.2 answers question 3.4 on whether packages of measures are more effective than individual measures.

Sections 6.1.3 and 6.3 speak to research question 3.8 (how does the model deal with uncertainty and how robust are the solutions generated). Research questions on the case study model, in particular, (questions 5.1 to 5.5) are addressed in Section 6.2. These questions include what measure combinations are preferred when viewed from different stakeholder perspectives (5.1), indicating how the Pareto optimal solutions differ from each other (5.2), determining whether there are any measures that are always preferred for inclusion at a particular level of implementation, or some that are never included (5.3), whether the model can illuminate the trade-offs that decision-makers need to debate (5.4) and whether the findings produced can be generalised into rules of thumb in the freight energy management arena (5.5).

The quality of the solution found (question 3.7) is discussed in terms of the quality of the Pareto front generated in Section 6.1.1, while the quality of the decision support provided by the tool is discussed in Section 6.2 – addressing question 4.1 (does the decision support tool provide valuable decision support). An outlay of how the outputs from the decision support tool facilitate better decision-making (question 4.2) is provided at the end of Section 6.1.1 and the analysis in Section 6.2 practically demonstrates the nature of the decision support developed by the FTEMT. The operational validation of the tool, discussed throughout this chapter, serves as a positive answer to the question on whether the tool is practical to use for its intended purpose (question 4.3).

7 Conclusions and Potential Future Research

7.1 Reflection on the Research Objective

The key problem addressed in this dissertation is how to manage and address the complexity involved in the development of a holistic, sustainable and comprehensive government level freight energy mitigation strategy. The objective was to develop a decision support tool that provides a useful solution to this problem, by producing decision support which encapsulates and addresses all the underlying issues and complexities of the problem, on behalf of the decision-makers. The Freight Transport Energy Management Tool (FTEMT) developed successfully achieves this stated objective.

7.2 Strengths of the FTEMT

The decision support produced by the FTEMT reduces the burden on decision-makers, freeing up resources to debate national priorities when deciding on a course of action. The tool eliminates the need for decision-makers to factor in the problem complexities during the decision-making process – a virtually impossible feat, due to the scale and level of complexity in question – by accounting for said complexities during the development of its decision support outputs. Decision-makers only need to consider the output produced by the tool and can have confidence that the reduced set of options they need to consider has been developed subject to the restrictions that the problem complexities place on the development of decision alternatives. Any of the proposed options presented to the decision-makers are, thus, viable for selection and decision-makers only need to use their discretion in terms of selecting a preferred option. Use of the tool facilitates good decision-making by doing that which human decision-makers are not able to effectively do: ensure that the problem complexities are properly accounted for and consider the full scale of the problem.

An additional benefit of using the tool to generate alternatives to choose from is that, due to the high level of complexity embedded within the tool, it is difficult for decision-makers to manipulate or tamper with the alternatives to fit their own agendas. Decision-makers can apply bias when choosing their preferred option from the set of equally good alternatives produced, but not during the development of the alternatives contained in that set.

The optimisation algorithm in the FTEMT allows the tool to be virtually unrestricted in terms of its ability to explore the search space, whilst producing a finite set of alternative options to be considered by the decision-makers. As a result, the decision space that decision-makers are confronted with is small and manageable to interrogate in detail when deciding on a preferred solution for implementation, although the entire search space has been explored to produce this result. In practice, time and computational resource limitations prevent any algorithm from fully exploring an infinite search space, but metaheuristic algorithms (such as the AMOSA algorithm adopted in the FTEMT) have been proven to allow sufficient exploration in a limited number of steps to identify solutions representative of the optimal solution, with a high level of confidence in the quality of the solutions.

As the multi-objective optimisation approach in the AMOSA algorithm does not produce a single suggested solution (it produces a set of Pareto optimal solutions), trade-offs between solutions that need to be navigated by decision-makers are clearly exposed. Every solution in this Pareto set reveals a specific, synergistic combination of freight energy management measures to the decision-makers, supporting the development of comprehensive freight energy management strategies.

The simulation model sub-component of the FTEMT is effectively a network assignment model that determines the split of freight transport between modes, routes, vehicles, propulsion systems and energy sources. The final network allocation (in tkm per mode, route, vehicle, propulsion system and energy source, respectively) is used to calculate the impacts of the specific transport assignment on the various decision objectives. The objectives are all calculated in terms of freight transport volumes (tkm), allowing for an unbiased and consistent comparison between solutions. Every freight energy management measure is translated into its impact on the transport assignment problem – either changing the assignment options available in the simulation model, changing the actual assignment decisions made, or changing the formulae used to assess the impact of an assignment on the objectives. This conversion of each measure into an impact on the total tkm per mode, route, vehicle, propulsion system and energy source, or an impact on the assessment of the tkm assignment, is what allows such a vast range of heterogenous measures (and, potentially, measures that have not been conceived yet) to be combined in a single solution. The network assignment corresponding to each solution provides decision-makers with an indication of the extent to which each measure is applied in this particular combination. Additionally, the hierarchical structure of the simulation model and its sequential network assignment process enables the tool to take the effects of measures on each other into account, by limiting the range of assignment options of dependent decisions downstream. This structure also enables the assessment of the system-wide impacts of each measure, as the decision in terms of each measure has a ripple effect on the total network allocation.

The complexities facing the development of freight energy management strategies discussed in the problem statement (Section 1.2) are, thus, addressed in either the optimisation or simulation component of the FTEMT.

Another major strength of the FTEMT is the high level of stakeholder involvement that is encouraged during every step of its development, ensuring stakeholder buy-in and proper understanding of the results. Decision-makers are familiar with the model and are satisfied that the model specification is fit for purpose before they are presented with the results, fostering high levels of confidence in the decisions that they make based on the decision support provided.

7.3 Weaknesses of the FTEMT

As with any model, the simulation model in the FTEMT is merely a simplification of the real world and the relationships between entities within the freight network and can, therefore, not be regarded as a hundred percent accurate reflection of interactions within the freight system. Due to the complex nature of the problem and the vast amount of information that needs to be considered, however, an imperfect modelling answer provides more insight and facilitates decision-making better than no guidance or decision support at all. Although there is no way to get around the need for simplification of the problem, the validation of the FTEMT shows that the decision support produced is reasonable and reliable enough to be useful. The FTEMT, thus, provides valuable decision support to a difficult problem.

7.4 Opportunities for FTEMT Improvement and Further Research

The case study model specification presented in this document is an example of a highly restrained problem formulation that proves to be operationally valid and that produces insightful, meaningful results. Many ways and means can, however, be identified in which the case study model formulation (and, thus, the FTEMT) can be improved upon. It is postulated that each improvement will yield better decision support and improve upon the understanding of the problem, however, it is recognised that a real-world application of the FTEMT will be invaluable in terms of furthering its development.

A suggestion for the improvement and expansion of the case study model from a transportation planning perspective is to expand the impact assessment formulae to also account for the indirect sustainability impacts generated by the production of the energy and vehicles needed to facilitate the freight transport assigned in the network, or during the construction of the infrastructure required in the network. Likewise, the assessment criteria of all three objectives can be expanded to be more comprehensive. For instance, the social objective assessment metric can be expanded to include transport safety criteria as well. Another suggestion is to expand the scope of the model to include urban freight. The FTEMT can potentially be modified to not only provide decision support for freight energy related problems, but for other freight management problems as well. Furthermore, the model premise can be applied to the passenger transport arena - a similar tool can be developed for passenger transport. Such a passenger transport energy management tool could then be integrated with the FTEMT to form an overall transport energy management decision support tool. Another interesting idea would be to couple the FTEMT to a demand forecasting model, in order to investigate the robustness of policies, should structural changes to freight demand in the network come into effect. Finally, the formulation of all model sub-components at all model levels (e.g. per mode, per decision variable, per objective function) can be revised and improved upon. Specific examples of this could be to improve the routing algorithm used, to include pipelines as an additional freight mode, to improve on the evaluation of the sustainability impacts of air transport, to improve the empty running algorithm, or to expand the demand and scope of the model to include more commodities and a larger network specification (more origins and destinations).

From an operations research point of view, the case study model can be adapted to increase its exploration capabilities further. The effect of the use of a fixed archive size through clustering (as suggested in the original AMOSA algorithm) can be explored, or the effect of accepting all non-dominated solutions found during the hill-climbing process, instead of only accepting strictly dominant solutions. In terms of the development of operations research theory, other multi-objective metaheuristic algorithms can be compared to AMOSA for use in the FTEMT to see if they produce better results faster. The problem described in this dissertation can serve as a practical problem to be solved with these other algorithms, which will advance the state of knowledge on their usefulness at solving real-world problems, ultimately aiding future multi-objective optimisation algorithmic development.

The list of suggested improvements to the case study model and research avenues to explore presented here is by no means comprehensive, yet it serves to illustrate the potential for research and development of the tool that has been unlocked through the development of this initial version of the FTEMT.

7.5 Threats for Application of the FTEMT

The high volume of data required to populate the FTEMT poses its biggest challenge. Balancing the level of detail included with a model's ability to realistically and accurately represent the real world is a standard modelling conundrum. Decision-makers, however, have complete control in setting this balance in the FTEMT, because the FTEMT is extremely scalable. If the data requirements associated with their desired model specification are impractical (either because of a lack of available and reliable data, or because of the sheer volume of data that will be required to match the problem specification), the model can be curtailed to the extent that data availability allows. This curtailment does not have to be uniform over all model components (for example over all modes, or for all the objective function specifications). The specification of different model components can be improved and expanded piecewise over time (if new data becomes available, for instance) without a loss to model integrity. In fact, the practice of developing a basic, simple version of a large scale, complex model, initially, then improving model components individually, over time, is a recognised and prudent modelling approach for large scale simulation models, such as the FTEMT. If the basic version of the model works and produces valid results, the model premise will be valid for a version of the model with more intricate specifications of the model components and formulae, as well.

Although the initial adaptation of the FTEMT for a specific application is very resource intensive, this is a once-off investment. When the tool has been configured to the satisfaction of the decision-makers, it can be used over and over again, without the need for further resource investment. Every time the tool is consulted for decision support, the initial investment becomes more worthwhile. The tool specification will organically evolve and improve over time through multiple use cycles, making it more valuable with each application.

As the model specification grows, however, so will the required amount of input data. Any increase to the scale of the tool and, consequently, the level of detail covered by the tool, will have a marked impact on the runtime of the tool. A long runtime is acceptable, and perhaps even expected, for a strategic model such as this. Figure 7.1 demonstrates that strategic level problems typically have a requirement for long search times and high-quality solutions. This is due to the fact that decision-makers need to live with the impact of their decisions for a long time in these kinds of problems. There are, however, still practical limits to what the runtime can be, at this point in time, imposing a limitation on the quality of solutions that are practical to find. The potential exists that this restriction might not always be in effect, however. If computing power continues to progress as it historically did (Figure 7.2), large-scale, ambitious models (such as the FTEMT) might become the norm. Any developments and improvements in terms of model specifications made now will be of great value should this occur, when more ambitious model designs will become practicable. Until then, though, there are methods to decrease the model runtime that can be explored. These include experimenting with a faster multi-objective optimisation algorithm, improving the actual coding of the problem, modifying the code to make use of parallel processing and even making use of cloud-based supercomputers.

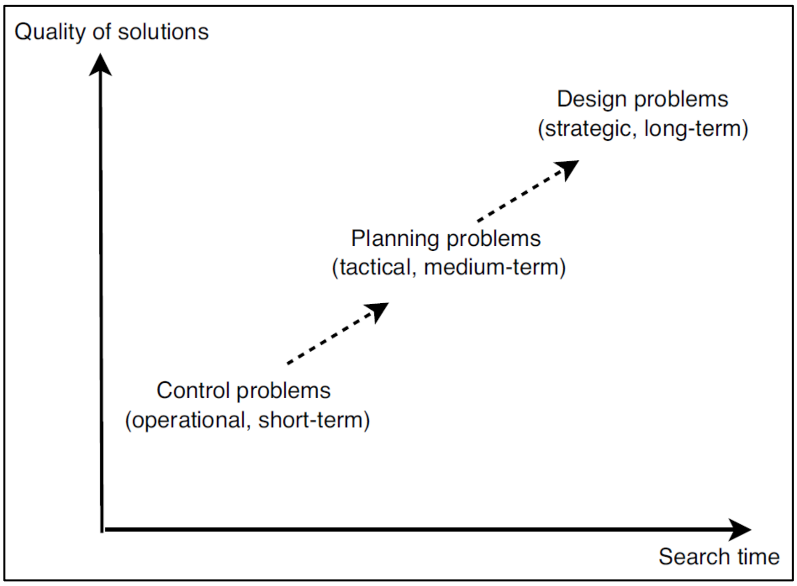


Figure 7.1 Decision problem classification in terms of the trade-off between quality of solutions and search time (Talbi, 2009)

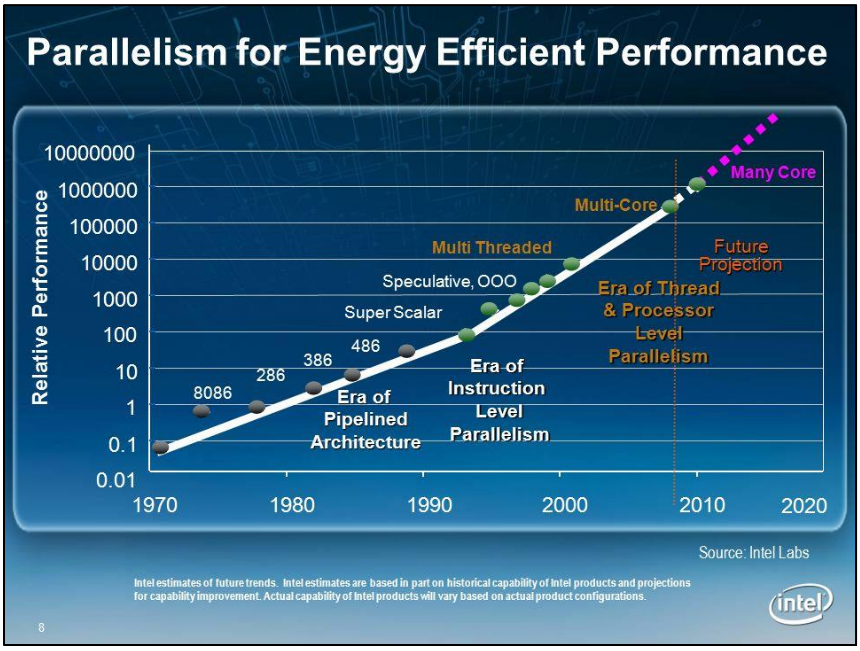


Figure 7.2 The historical progression of Intel processor performance (Pawlowski, 2009)

A summary of the strengths, weaknesses, opportunities and threats of the FTEMT is provided in Appendix F.

7.6 Contribution to Science

Development of the FTEMT drew on knowledge from the sustainable transport planning, traditional transportation modelling and operations research domains. In fact, it was the combination of this knowledge from different domains that culminated in the decision support tool presented in this dissertation. The use of simulation optimisation as the foundation of the FTEMT is instrumental to the tool's ability to manage and address the complexities associated with the development of sound freight energy management strategies. The optimisation component and the tool development process reside within the operations research domain, whereas the simulation component drew on knowledge from the sustainable transport planning, traditional transport modelling and operations research domains.

7.7 Chapter Summary

It can be concluded that proper freight transport energy management is important, but it is difficult to know how to achieve this. It is imperative that decision-makers get it right, yet the complex nature of the problem leaves them in need of sound decision support. The Freight Transport Energy Management Tool developed in this dissertation is a step in the right direction – it proposes a suitable, effective methodology for the development of the required decision support. Moreover, the work presented serves as a basis to stimulate further scholarship (as demonstrated by the number of research opportunities unlocked related to the improvement of the case study version of the FTEMT) and it expands upon the collective knowledge on the topic, by proposing an approach that is able to address the full scale of complexities involved in the production of decision support on the development of freight energy management policy.

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Appendix A - Transport Energy Mitigation Measures

This appendix contains a summary table (Table A1) of potential green economy investment measures and an assessment of the measures' potential economic, social and environmental impacts, as published in Dalkmann *et al.* (2011). Estimates on the timeframes to realise impacts and the ease of implementation of each measure is also provided.

The second table included in this appendix (Table A2) is published in Sims *et al.* (2014) and summarises the mitigation options in freight transport discussed in the document.

Table A1 Summary table of green economy investment measures (Dalkmann et al., 2011)

CATEGORY	MEASURE	DESCRIPTION	ECONOMIC	SOCIAL/HUMAN[1]	ENVIRONMENT	TIMEFRAME	EASE OF IMPLEMENTATION
POLICIES[2]	LAND-USE PLANNING URBAN DESIGN	COMPACT AND CORRIDOR BASED CITIES PLANNING, LAND-USE MIX, TRANSIT ORIENTATED DEVELOPMENT, RESTRICTED AREAS	MODERATE TO HIGH	• URBAN ACCESS • HEALTH	HIGH	LONG	LOW
	STANDARDS	FUEL QUALITY, EMISSIONS, ALTERNATIVE FUEL SOURCES, RENEWABLE ENERGY,VEHICLE DESIGN	LOW	• HEALTH	HIGH	SHORT TO MEDIUM	MODERATE TO HIGH
	TAXES AND CHARGES	FUEL TAX, VEHICLE OWNERSHIP TAX, ROAD TAX, COMPANY CAR TAX, CARBON TAX, CONGESTION PRICING/TOLLING, LANDFILL TAX	MODERATE	• *DISPOSABLE INCOME*	LOW	SHORT TO MEDIUM	MODERATE TO HIGH
	FINANCIAL INCENTIVES/SUBSIDIES	CLEAN VEHICLE REBATE, PUBLIC TRANSPORT REBATE, BICYCLE PURCHASING BENEFIT, SCRAPPAGE ALLOWANCE, PUBLIC TRANSPORT, EMPLOYER GRANTS	LOW TO MODERATE	• DISPOSABLE INCOME	LOW	SHORT TO MEDIUM	MODERATE TO HIGH
	POLICY PUSH	PROMOTION OF PUBLIC TRANSPORT - INCLUDING PARK&RIDE, NON-MOTORISED TRANSPORT, PARKING POLICIES, CAR-POOLING, GREEN WHEELS, RAIL BASED FREIGHT, E-WORKING, E-LEARNING ETC AND RECYCLING, VEHICLE MAINTENANCE (ROADWORTHINESS)	LOW	• ACCESS • HEALTH • AVAILABLE TIME	MEDIUM	MEDIUM	MODERATE
INSTITUTIONS/ GOVERNANCE	STAFF TRAINING	CONTINUED PROFESSIONAL DEVELOPMENT, TRAFFIC MANAGEMENT,	LOW	• HEALTH	MEDIUM	SHORT TO MEDIUM	HIGH
	CAPACITY BUILDING	TRAINING, EDUCATION, BURSARIES	LOW TO MODERATE	• JOB CREATION	MEDIUM	SHORT TO MEDIUM	HIGH
	CAMPAIGNS	DRIVER BEHAVIOUR, REDUCED USE OF ACCESSORIES, TDM, VEHICLE MAINTENANCE	LOW	• DISPOSABLE INCOME • HEALTH • JOB CREATION	MEDIUM TO HIGH	MEDIUM	MODERATE TO HIGH
	ENFORCEMENT	TARGETS, AUDITS, ROAD BLOCKS	N/A	N/A	N/A	SHORT	HIGH
INFRASTRUCTURE	AIR	AIRPORT BUILDING DESIGN, PUBLIC TRANSPORT	MODERATE	• ACCESS	MEDIUM	LONG	LOW

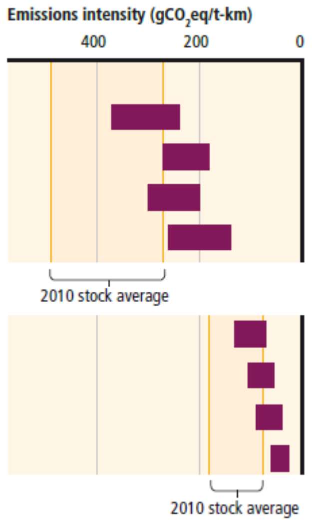
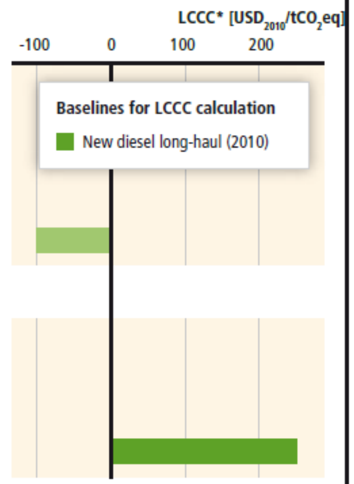
		INTEGRATION, RUNWAY DESIGN OPTIMASATION	TO HIGH	• HEALTH • LIVEABILITY			TO MODERATE
	RAIL	STATION IMPROVEMENTS, NETWORK DESIGN	MODERATE TO HIGH	• ACCESS			
	PIPELINE	NETWORK DESIGN	MODERATE TO HIGH	• HEALTH			
	WATER	HARBOUR IMPROVEMENTS	MODERATE TO HIGH	NEUTRAL			
	ROAD	PRIMARY AND SECONDARY NETWORK DESIGN (ALL ROAD MODE INCLUSIVE), TERMINALS AND STATIONS FOR PUBLIC TRANSPORT, PARA-TRANSIT AND NMT, PARKING FACILITIES, SCRAP WARDS,RECYCLING FACILITIES, ITS HARDWARE	MODERATE TO HIGH	• ACCESS • HEALTH • LIVEABILITY			
	MAINTENANCE OF INFRASTRUCTURE	ASSET REGISTER, CODITION SURVEYS, ROUTINE MAINTENANCE PROGRAMS, RENEWAL STRATEGIES	LOW TO MODERATE	• DISPOSABLE INCOME • SAFETY	LOW TO MEDIUM	SHORT	HIGH
	FUTURE SYSTEM INFRASTRUCTURE	MAGLEV	MODERATE TO HIGH	• ACCESS • HEALTH • AVAILABLE TIME	HIGH	LONG	LOW
	CLEAN ENERGY INFRASTRUCTURE	RECHARGE FACILITIES FOR ELECTRIC VEHICLES, HYDROGEN, HIBRID, LPG, VEGETABLE OIL	MODERATE TO HIGH	• HEALTH	HIGH	LONG	LOW TO MODERATE
	TRANSFERIA	INTERMODAL FACILITIES	MODERATE TO HIGH	• ACCESS • DISPOSABLE INCOME • SAFETY/SECURITY	MEDIUM	MEDIUM TO LONG	MODERATE TO HIGH

OPERATIONS	AIR TRAFFIC MANAGEMENT	REDUCING TAXI TIME, CHANGING HOLDING PATTERNS, SCHEDULING, IMPROVE OCCUPANCY AND LOADS	LOW TO MODERATE	• AVAILABLE TIME • RELIABILITY	MEDIUM TO HIGH	SHORT	HIGH
	RAIL TRAFFIC MANAGEMENT	REDUCED IDLING, ROUTING AND SCHEDULING, ROLL-ON-ROLL-OFF	LOW TO MODERATE				
	HARBOUR MANAGEMENT	FREIGHT TRANSPORT HANDLING, SCHEDULING	LOW TO MODERATE				
	TRAFFIC MANAGEMENT	SCOOT, TRAFFIC INFORMATION/MANAGEMENT CENTRES, INCIDENT MANAGEMENT, PUBLIC TRANSPORT PRIORITY, PARKING MANAGEMENT	LOW TO MODERATE				
	PARA-TRANSIT	TICKETING	LOW	NEUTRAL	LOW	SHORT TO MEDIUM	HIGH
	NON-MOTORISED TRANSPORT	PARKING FACILITIES	LOW	• ACCESS • SECURITY • *DISPOSABLE INCOME*	LOW	SHORT	HIGH
	ROAD BASED PUBLIC TRANSPORT MANAGEMENT	BUS OPERATOR MANAGEMENT SYSTEMS (ROUTING AND SCHEDULING, MAINTENANCE)	LOW TO MODERATE	• AVAILABLE TIME • RELIABILITY	LOW TO MEDIUM	SHORT	HIGH
	FLEET MANAGEMENT/ TRACKING	AIR, RAIL, WATER, ROAD, PIPELINE	LOW TO MODERATE	• RELIABILITY	MEDIUM	SHORT	HIGH
	OCCUPANCY/LOAD MANAGEMENT/ VEHICLE SIZING	REDUCTION OF EMPTY SPACES/TRIPS	LOW TO MODERATE	• ACCESS • HEALTH • AVAILABLE TIME	MEDIUM TO HIGH	MEDIUM	MODERATE
	STAFF TRAINING	PILOTS, ENGINEERS, CAPTAINS AND DRIVERS	LOW	NEUTRAL	LOW TO MEDIUM	SHORT	HIGH

TECHNOLOGY AND R&D	VEHICLE DESIGN (PLANES, TRAINS, BOATS AND ROAD VEHICLES)	THIS MEASURE INCLUDES THE INTRODUCTION OF SMALLER AND LIGHTER VEHICLES, LESS ROLLING AND AIR RESISTANCE, REGENERATIVE BRAKING	MODERATE TO HIGH IN FUTURE	• HEALTH • DISPOSABLE INCOME • SAFETY	HIGH	LONG	LOW
	INFRASTRUCTURE DESIGN	MAGLEV, TURBULAR FREIGHT	MODERATE TO HIGH IN FUTURE	• HEALTH			
	PROPULSION	IMPROVED ENGINE EFFICIENCY	MODERATE TO HIGH IN FUTURE	• HEALTH • DISPOSABLE INCOME			
	ALTERNATIVE PROPULSION	ELECTRIC VEHICLES, HYBRID VEHICLES, HYDROGEN VEHICLES AND MAGLEV SYSTEMS, BATTERIES	MODERATE TO HIGH IN FUTURE	• HEALTH			
	EMISSION REDUCTION	CATALISTS, FUELS, FUEL ADITIVES	MODERATE	• HEALTH	MEDIUM TO HIGH	SHORT TO MEDIUM	MODERATE
	RECYCLING	VEHICLE AND PARTS DESIGN	LOW TO MODERATE	NEUTRAL	MEDIUM	SHORT TO MEDIUM	MODERATE TO HIGH
	VEHICLE MAINTENANCE	DIAGNOSTIC SYSTEM DEVELOPMENT	LOW TO MODERATE	• HEALTH • DISPOSABLE INCOME • SAFETY	LOW TO MEDIUM	SHORT TO MEDIUM	MODERATE TO HIGH
	INTELLIGENT TRANSPORT SYSTEMS[4]	INFRASTRUCTURE BASED TELEMATICS	LOW TO MODERATE	• ACCESS • HEALTH • AVAILABLE TIME • RELIABILITY	MEDIUM	SHORT	LOW
	IN-CAR TELEMATICS	NAVIGATION SYSTEMS, FUEL ECONOMETERS, DRIVER ASSISTANCE TECHNOLOGY, CAR-2-CAR SYSTEMS, ADAPTIVE CRUISE CONTROL, INTELLIGENT SPEED ADAPTATION…	LOW TO MODERATE	• ACCESS • AVAILABLE TIME • RELIABILITY	LOW TO MEDIUM	SHORT TO MEDIUM	MODERATE TO HIGH
	TELE-COMMUNICATIONS	VIDEO STREAMING, GPS, PHONE…	LOW TO MODERATE	• DISPOSABLE INCOME • AVAILABLE TIME	MEDIUM TO HIGH	MEDIUM	MODERATE

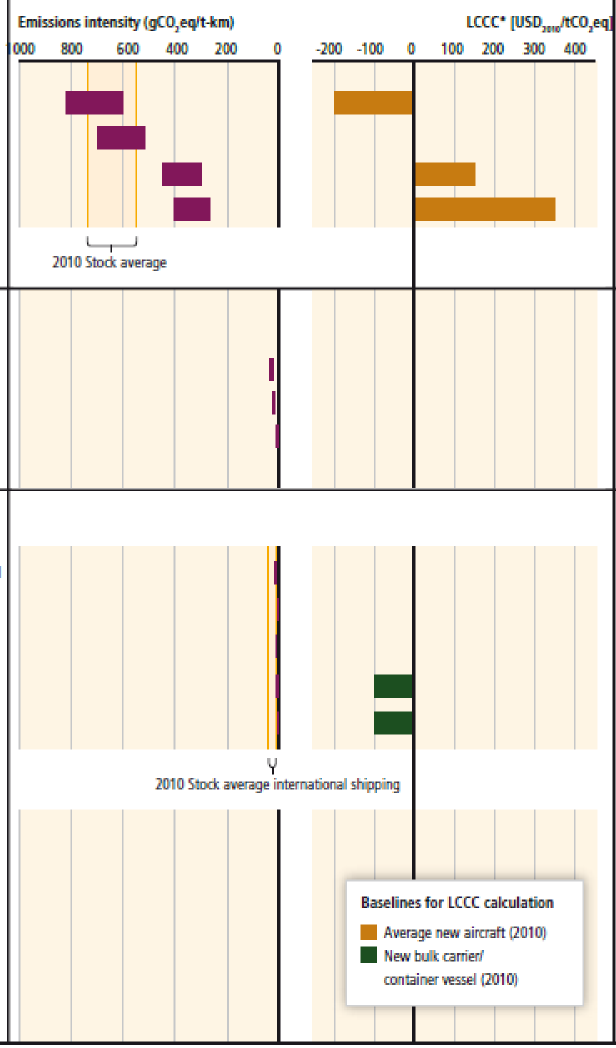
[1] ITALIC SCRIP REFERS TO A NEGATIVE IMPACT
[2] IMPACT OF POLICIES DEPENDS ON THE LEVEL OF ENFORCEMENT
[3] IMPACT DEPENDS ON CURRENT SKILLS LEVEL
[4] SUSTAINING AND IMPROVING BENEFITS

Table A2 Summary of mitigation options in freight transport (Sims et al., 2014)

Mitigation options in freight transport	Indicative 2010 stock average baseline CO_2eq emissions and reduction potential	Indicative direct mitigation cost in relation to the baseline (can be positive or negative)	Reference conditions and assumptions made	Illustrative examples
Road **New medium duty trucks** 2010 Diesel 2010 Diesel hybrid 2010 Compressed natural gas 2030 Diesel **New heavy duty, long-haul trucks** 2010 Diesel 2010 Compressed natural gas 2030 Diesel 2030 Diesel/biofuel (50/50 share)**			**Baseline stock average medium haul HDV** Diesel fuelled HDVs: 76–178 gCO_2/t-km (25). 55% improvement in energy efficiency of tractor trailer HDV between 2010 and 2030 and 50% for other categories of HDV (9, 10). 30–62% improvement by 2030 compared to a similar size 2007–2010 HDV, including increasing load factor by up to 32% (5, 11). Urban HDVs 30–50% reductions at 0–200 USD/tCO_2. Long-haul HDV up to 50% potential CO_2 reduction at negative costs per tCO_2 saved.	New diesel example (47) New diesel hybrid example (47) 'Green Trucks Project' Guangzhou, China, could save 8.6 billion l/yr of fuel and reduce CO_2 emissions by 22.3 $MtCO_2$/yr if all HDVs in the province participated (12). UK 'Logistics Carbon Reduction Scheme' comprising 78 businesses set target for reducing the target intensity of road freight transport by 8% between 2010 and 2015, which is likely to be achieved by the end of 2013.

*Levelized cost of conserved carbon (LCCC), here at 5% weighted average cost of capital (WACC)

**Assuming 70% Less CO_2eq/MJ Biofuel than /MJ Dies



Mitigation options in freight transport	Indicative 2010 stock average baseline CO_2eq emissions and reduction potential	Indicative direct mitigation cost in relation to the baseline (can be positive or negative)	Reference conditions and assumptions made	Illustrative examples
Aviation (Commercial, medium to long haul) 2010 Dedicated airfreighter 2010 Belly-hold 2030 Improved aircraft 2030 Improved, open rotor engine			See Passenger "Aviation" assumptions above Freight factors for wide-bodied passenger aircraft are around 15-30% whilst narrow bodied planes are typically 0-10% (52),	See Passenger "Aviation" examples above
Rail (freight train) 2010 Diesel, light goods 2010 Diesel, heavy goods 2010 Electric , 200 gCO_2eq/kWh			**Baseline** based on electricity grid 600 gCO_2/kWh: 6–33 gCO_2/t-km (25). - 40–45% reduction in CO_2/t-km (augmented if switch to low-carbon electricity). - 14% reduction in operating costs (allowing for increase in speed and with energy costs excluded from cost calculation) (38). Also see passenger "Rail (Light Rail Car)" above.	See passenger "Rail (Light Rail Car)" above
Waterborne 2010 New large international container vessel 2010 Large bulk carrier/tanker 2010 LNG bulk carrier 2030 Optimized container vessel 2030 Optimized bulk carrier			**Baseline: Stock average international ships** 10–40 gCO_2/t-km (25). **2010 water craft:** 5–30% CO_2/t-km reduction potential; retrofit and maintenance measures 2–20%; total reduction 43% (2020) to 63% (2050) (19). Potential up to 60% CO_2 reduction by 2030 from optimized technology and operation (19). 30% or more reduction in CO_2/t-km by 2030 at zero cost (30). **2030 water craft:** Business-as-usual reduction in carbon intensity of shipping of 20% between 2010 and 2030 but could rise to 37% with industry initiatives (39).	2010 new medium vessel:(46) Industry initiatives through the Energy Efficiency Design Index and Ship Energy Efficiency Management Programme of the International Maritime Organisation (IMO)(22)
Water craft operations and logistics Slow steaming of container vessel Inland waterways			**Operations:** Potential CO_2 reductions 15–39%; Slow steaming at 3–9kts slower than 24kt baseline. **Cost savings** around 200 USD/tCO_2 at bunker fuel price of 700 USD/t and combining savings for carriers and shippers (37). CO_2 emissions reductions of 43% per t-km by 2020 (20); - 63% CO_2/t-km by 2050 (21); - 25–75% GHG intensity by 2050 (22); - 39–57 % CO_2/t-km 'attainable' by 2050; - 59–72 % CO_2/t-km is 'optimistic' by 2050 (23)	Global average speed reduction of 15% would give benefits that outweigh costs by 178–617 billion USD by 2050 (31). 'Slow steaming' at 10% slower speed gives 15–19% CO_2 emissions reduction; 20% slower speed gives 36–39% (24, 31, 37). Inland waterways potential (46)

*Levelized cost of conserved carbon (LCCC), here at 5% weighted average cost of capital (WACC)

Cross-modal mitigation options	Indicative 2010 stock average baseline CO_2eq emissions and reduction potential	Indicative direct mitigation cost in relation to the baseline (can be positive or negative)	Reference conditions and assumptions made	Illustrative examples
Biofuels	Broad range	Broad range	0–100% excluding land use change effects (26, 33). GHG reduction potential by fuel type: - sugarcane ethanol: 0–80% - enzymatic hydrolysis ethanol: 0–100% - advanced biomass-to-liquid processes (direct gasoline/diesel replacements): 0–100% (33). 80 USD/tCO_2 for biofuels with 80% lower net GHG emissions and 20% higher cost per litre gasoline equivalent (lge) than base fuel (e.g., gasoline).	Brazilian sugarcane: 80% GHG emissions reduction compared with gasoline (excluding land use change effects) (33).
Logistics and freight operations			13–330 USD/tCO_2 (26, 28). ~18% reduction in CO_2/t-km possible from: - speed reduction (7 percentage points) - optimized networks (5 percentage points) - modal switch (4 percentage points) - increased home delivery (1 percentage point) - reduced congestion (1 percentage point) (27).	UK Government best practice programme for freight/logistics at –12 USD/tCO_2 (28). Low-carbon technologies for urban and long-haul road freight –67–110 USD/tCO_2; Route management: ~330 USD/tCO_2.
Eco-driving and driver education			Negative costs per tCO_2 saved even with on-board eco-drive assistance technologies and meters (32). 5–10% reduced fuel consumption (50) 5–25% reduced fuel consumption (15, 16).	Japan: 12% fuel consumption savings through eco-driving-schemes in freight (12).
Activity reduction in urban areas			GHG reduction of up to 30% (29, 40, 41)	Urban densification in the USA over about 50 years could reduce fuel use by 9–16% (35).

Selected CO_2eq mitigation potentials resulting from changes in transport modes with different emission intensities (tCO_2eq/p-km or /t-km) and associated levelized cost of conserved carbon (LCCC in USD_{2010}/tCO_2eq saved). Estimates are indicative. Variations in emission intensities stem from variation in vehicle efficiencies and occupancy/load rates. Estimated LCCC for passenger road transport options are point estimates ±100 USD_{2010}/tCO_2eq based on central estimates of input parameters that are very sensitive to assumptions (e.g., specific improvement in vehicle fuel economy to 2030, specific biofuel CO_2eq intensity, vehicle costs, fuel prices). They are derived relative to different baselines (see legend for colour coding) and need to be interpreted accordingly. Estimates for 2030 are based on projections from recent studies, but remain inherently uncertain. LCCC for aviation and for freight transport are taken directly from the literature. Additional context to these estimates is provided in the two right-most columns of the table (see Annex III, Section A.III.3 for data and assumptions on emission intensities and cost calculations and Annex II, Section A.II.3.1 for methodological issues on levelized cost metrics).

References: 1: IATA (2009), 2: TOSCA (2011), IEA (2009), 3: Dell'Olmo and Lulli (2003), Pyrialakou et al. (2012), 4: Bandivadekar (2008), ICCT (2010), Greene and Plotkin (2011), IEA (2012a), 5: IEA (2012), 6: NRC (2011a), 7: Sims et al. (2011), 8: Chandler et al. (2006), 9: ICCT (2010), NRC (2010), IEA (2012e), 10: ICCT. (2012), 11: NRC (2012), 12: UNEP (2011), 13: Chandler et al. (2006), IPCC (2007), AEA (2011), ITF (2011), IEA (2012d), 14: Hallmark et al. (2013), 15: Goodwin and Lyons (2010), Taylor and Philp (2010), Ashton-Graham et al. (2011), Höjer et al. (2011), Salter et al. (2011), Pandey (2006), 16: Behrendt et al. (2010), 17: Argonne National Lab. (2013), 18: UIC (2011), 19: IEA (2011a), 20: Crist (2009), IMO (2009), DNV (2010), ICCT (2011b), Lloyds Register and DNV (2011), Eide et al. (2011), 21: Crist (2009), 22: IMO (2009), 23: Lloyds Register and DNV (2011), 24: DNV (2010), 25: TIAX (2009), IEA (2012c), 26: Lawson et al. (2007), AEA (2011), 27: World Economic Forum/Accenture (2009), 28: Lawson et al. (2007), 29: TFL (2007), Eliasson (2008), Creutzig and He (2009), 30: IMO (2009), 31: Faber et al. (2012), 32: IEA (2009), IEA (2010b), 33: Bioenergy Annex, Chapter 11; 34: TOSCA (2011), 35: Marshall (2011), 36: ITDP (2009), 37: Maloni et al. (2013), 38: Andersson et al. (2011), 39: Wang (2012b), 40: Sælensminde (2004), 41: Tirachini and Hensher (2012), 42: DfT (2010), 43: Andersson et al. (2011), 44: Halzedine et al. (2009), 45: Sharpe (2010), 46: Skinner et al. (2010a), 47: Hill et al. (2012), 48: IEA (2012c), 49: Freight Transport Association (2013), 50: SAFED 2013; 51: NTM (2011), 52: Jardine (2009).

Appendix B - Decision-Making and Operations Research

Decision-making is the process of making choices by identifying a decision, gathering information and assessing alternative solutions. The University of Massachusetts identify seven steps to effective decision-making (UMass Dartmouth, 2018):

1. Identify the decision
2. Gather information
3. Identify alternatives
4. Weigh the evidence
5. Choose among alternatives
6. Take action
7. Review your decision

Improving and understanding the process of making strategic decisions has emerged as one of the most important themes of strategy research over the last two decades (Papadakis, 2006). Failure to adopt a logical process for strategy development can impose a barrier to effective planning (May *et al.*, 2005). That is why guidelines and methods developed for decision-making focus on the collection, analysis and presentation of objective information on the basis of which the decision-maker can improve his or her judgement (Kørnøv and Thissen, 2000).

The context within which the decision has to be made is of paramount importance and needs to influence the decision-making process. This notion is supported by Zeleny (1982), as he indicates that no individual decision-making process is completely independent of the social or collective framework in which it takes place. He advises that you should not concentrate on the pursuit of your own objectives, without acknowledging the impact of your decisions on others, or without understanding how actions taken elsewhere influence the effectiveness of your efforts. “Effective best practices are developed based on the conditions faced by a specific decision-maker, such as local fuel costs. It is critical to develop a decision support framework that will allow parties to compare multiple best practices on the basis of representative and relevant important assumptions” (Frey and Kuo, 2007).

This is one of the reasons why stakeholder involvement is recommended in the decision-making process (Zeleny, 1982; May *et al.*, 2005; Kørnøv and Thissen, 2000). Through stakeholder participation, the various objectives and priorities of different stakeholders can become known and taken into account. This enables the development of a common understanding of the objectives, the problems to be tackled, the possible solution strategies and the proposed implementation sequence (May *et al.*, 2005). Failure to adopt a participative approach to policy development can result in a lack of support among those who were involved in the implementation phase, but not in the decision-making phase (Kørnøv and Thissen, 2000) – another strong argument for continued stakeholder involvement.

Rationality, defined as the extent to which the decision-making process reflects a desire to make the best decision possible, under the circumstances, is another key concept in strategic decision-making (Musso and Francioni, 2012). Early studies of policy making highlighted two extreme approaches to decisions: a rational, analytical approach, which leads inexorably to the "right" solution, and a less organised approach, in which objectives are never specified, remedial action is taken when it becomes essential and more important decisions are dependent on the power struggles between interest groups (May *et al.*, 2005). It is found that the second approach is "unlikely to be effective in tackling the challenges of unsustainability" (May *et al.*, 2005). An extreme reliance on analysis is, however, also inappropriate in a situation in which priorities and preferences differ and outcomes are uncertain. Practical approaches between these two extremes (i.e. the use of a combination of an analytical tool and stakeholder involvement) is advised.

There are three standard approaches to decision-making in the urban planning context, which can be translated to other planning decision contexts: vision-led, plan-led and consensus-led approaches (May *et al.*, 2005). "Vision-led approaches usually involve an individual having a clear view of the future form of city they want, and the policy instruments needed to achieve that vision". The focus, when using this approach, is on implementing the required policy instruments as effectively as possible. This approach is critically dependent on the individual with the vision but, in practice, relatively few decision-making situations have a visionary leader in this sense (May *et al.*, 2005).

Plan-led approaches, in turn, involve specifying objectives and problems and adopting an ordered procedure identifying possible solutions to these problems and selecting those which perform best. Consensus-led approaches involve discussions between the stakeholders to try to reach agreement on each of the stages in the plan-led approach. Ideally, agreement is needed on the objectives to be pursued and their relative importance, the problems to be tackled and their seriousness, the policy instruments to be considered and their appropriateness, the selection of policy instruments which best meet the objective and the way in which they should be combined into an overall strategy and implemented. A combination of approaches is often deemed the best option, as difficulty to quickly reach and sustain agreement between stakeholders may lead to delays and inaction in a pure consensus-led approach (May *et al.*, 2005).

Whilst stakeholder involvement typically produces a subjectively formed list of criteria, most decision-making studies advocate the use of objective assessments in terms of the decision criteria. Supporting this ideal, decision support systems are often developed and implemented to help managers use data and models to support (rather than to replace) their decision-making (Hillier and Lieberman, 2010).

Operations research is a scientific approach to decision-making that seeks to best design and operate a system, usually under conditions requiring the allocation of scarce resources (Winston, 2004). This scientific approach to decision-making generally involves the use of one or more mathematical models. A mathematical model is a mathematical representation of an actual situation that may be used to make better decisions, or simply to understand the actual situation better (Winston, 2004). It is the collection of variables and relationships needed to describe pertinent features of a problem (Rardin, 1998). Otherwise stated, operations research is the study of how to form mathematical models of complex engineering and management problems and how to analyse them to gain insight to possible solutions (Rardin, 1998), making it the appropriate scientific discipline from which to approach this research.

The Standardised Operations Research Process

Decision-making is not a solitary act of selecting the most desirable alternative; rather it is a process (Zeleny, 1982). Hillier and Lieberman (2010) state that: "By its very nature, operations research requires considerable ingenuity and innovation, so it is impossible to write down any standard procedure that should always be followed by operations research teams." Regardless, several texts propose common elements of a standard operations research process. This section describes a standardised operations research process methodology, developed as a synthesis of the published process methodologies in Zeleny (1982), Winston (2004), Taha (2003), Rardin (1998), May *et al.* (2005), Hillier and Lieberman (2010) and Harrisson (1996). Figure 1.7 summarises this standardised operations research process. The process is divided into four stages, each with several steps to be followed, corresponding to Zeleny's (1982) theory that decision support is a dynamic and interrelated unity of pre-decision, decision and post-decision stages.

As mentioned earlier in this chapter, stakeholder involvement is a critical component to decision-making and, thus, to any standardised operations research process. May *et al.* (2005) advise that a decision on whether and how to employ stakeholder participation is best taken when the strategy formulation process is being designed. They also recommend being clear on the objectives of the participation at each stage of the decision-making process. The steps where stakeholder participation should be encouraged are explicitly indicated by a stakeholder icon in Figure 1.7. Identification of the stakeholders to involve in this process is very important. Kørnøv and Thissen (2000) suggest that the list of stakeholders that should be included may be determined by their formal position (for instance local government), their control of relevant resources (for instance money or expertise), their power to hinder or block implementation (such as lobby groups) or by their stakes in the issue.

Stage 1: The pre-decision stage

The first step during the pre-decision stage is to properly identify and understand the problem. While early decision-making literature paid a lot of attention to assessing the impacts of decision alternatives and choosing among a given set of alternatives with known outcomes (such as in cost-benefit analysis or decision analysis), later publications in this thread of thinking broaden the approach to paying significantly more attention to formulating the problem, identifying the values of interest and identifying a wide enough range of alternatives (Kørnøv and Thissen, 2000).

The scope of the problem needs to be defined, following which a determination of the three principle elements of the decision problem should be completed (Taha, 2003). The first principle element is the array of decision alternatives that the decision-makers are allowed to pursue (Rardin, 1998). The variables whose values are under the decision-maker's control and influence the performance of the system, are called *decision variables* (Winston, 2004).

The second element to be determined is the criteria that will be used to assess whether one selected value of the decision variable will be preferred over another (Rardin, 1998). These criteria are later used, along with the decision variables, to construct the *objective function* of the model (Taha, 2003). The objective function is a quantification of the relationships needed to describe the relevant system behaviour (Rardin, 1998).

Principle element number three represents the restrictions that limit the decision choices (Rardin, 1998). These restrictions, expressed as quantified relationships between the decision variables and external limiting parameter values, are known as the model *constraints* (Taha, 2003).

A fourth element that deserves some attention during the problem formulation step, is the collection of data required for the estimation of the *parameters* used in the objective function and in the constraints (Winston, 2004; Hillier and Lieberman, 2010). Hillier and Lieberman (2010) mention that an operations research team will, typically, spend a considerable amount of time trying to improve the precision of the data and will then, ultimately, make do with the best that can be obtained.

Step two in the pre-decision stage is to convert the formulated problem (as developed in step one) into a mathematical representation of the problem (Winston, 2004; Hillier and Lieberman, 2010; Taha, 2003). The typical operations research model is delineated as follows (Hillier and Lieberman, 2010): if there are n quantifiable decisions to be made, they are represented as decision variables (say $x_1 to\ x_n$), whose respective values are to be determined. The appropriate measure of performance is then expressed as a mathematical function (P) of these decision variables (for example $P = 3x_1 + 2x_2 + \cdots + 5x_n$), which is called the objective function. Any restrictions on the values that can be assigned to these decision variables are also expressed mathematically, typically by means of inequalities or equations (for example, $x_1 + 3x_1x_2 + 2x_4 \leq 10$). Such mathematical expressions for the restrictions are called constraints. The constants (namely, the coefficients and right-hand side values) in the constraints and the objective function are called the parameters of the model. The mathematical model typically describes the problem of choosing the values of the decision variables that maximise or minimise the objective function, subject to the specified constraints.

If the mathematical relationships required are too complex to allow the determination (or formulation) of an analytic solution in this format, the operations research team may opt to simplify the model and use a heuristic approach, or the team may consider the use of simulation, if appropriate (Taha, 2003). In some cases, a combination of mathematical, simulation and heuristic models may be needed to formulate and solve the decision problem. On the other side of the spectrum it is important to realise that when faced with a single attribute, objective function, utility function or any other single aggregate measure of merit, there actually is no decision-making involved (Zeleny, 1982). This is because the decision here is implicit in the measurement and is made explicit by the subsequent search. If a score can be calculated for each possible alternative, it is fair to assume the alternative with the most favourable score will be chosen. A mechanical search, thus, replaces the decision-making process. “It is only when facing multiple attributes, objectives, criteria, functions, etc., that we can talk about decision-making and its theory” (Zeleny, 1982).

Stage 2: The partial decision stage

Subsequent to the pre-decision stage comes the decision stage (Zeleny, 1982). In this derived standardised process, the decision stage is split into two stages: the partial decision stage and the final decision stage. Mathematical skills and technology are, classically, applied in these stages to see what conclusions the model suggests (May *et al.*, 2005). “A mathematical model forms a bridge to the use of high-powered mathematical techniques and computers to analyse the problem" (Hillier and Lieberman, 2010). There are several types of tools and techniques that could potentially be used. "Though mathematics is a cornerstone of operations research, one should not 'jump' into using mathematical models until simpler approaches have been explored" (Taha, 2003). An operations research study should never start with bias toward using a specific mathematical model before its use can be justified. Step one in the partial decision stage (step three of the standardised operations research process) is to determine what the best tool or technique is to find a solution. This can only happen once the problem has been properly defined, as in step two of the pre-decision stage (Taha, 2003).

The fourth step in the standardised operations research process is to develop a computer-based procedure for deriving solutions to the problem (Hillier and Lieberman, 2010). The development of this procedure can draw on the wealth of literature on optimisation algorithms and other quantitative modelling tools available. Once the procedure has been developed, it should be verified and used to propose solutions to the problem (Winston, 2004; Hillier and Lieberman, 2010).

Stage 3: The final decision stage

When a proposed solution, or set of solutions, can be generated, the final decision stage commences. Determining the appropriate values to assign to the parameters of the model is both a critical and challenging part of a model-building process. The value assigned to a parameter is often, of necessity, only a rough estimate (Hillier and Lieberman, 2010). Because of the uncertainty about the true value of the parameter, it is important to analyse how the solution derived from the model would change (if at all) if the value assigned to the parameter were changed to other plausible parameter values. It is an attempt to gauge the robustness of the solution, should some of the assumptions in the data be incorrect. This process is referred to as sensitivity analysis (Taha, 2003) and constitutes step five of a standardised operations research process.

Any model is inherently a simplification of the system being studied. Figure B1 depicts the levels of abstraction that characterise the development of an operations research model, according to Taha (2003). "The assumed real world is abstracted from the real situation by concentrating on the dominant variables that control the behaviour of the real system. The model, being an abstraction of the assumed real world, expresses in an amenable manner the mathematical functions that represent the behaviour in the assumed system" (Taha, 2003). The key to a good model is to drop unnecessary detail and complexity. It cannot and should not try to account for everything (May *et al.*, 2005). It is unnecessary to include unimportant details or factors that have approximately the same effect for all the alternative courses of action considered (Hillier and Lieberman, 2010). It is not even necessary that the absolute magnitude of the measure of performance be approximately correct for the various alternatives, provided that their relative values (i.e. the differences between their values) are sufficiently precise. Thus, all that is required is that there be a high correlation between the prediction by the model and what would actually happen in the real world (Hillier and Lieberman, 2010).

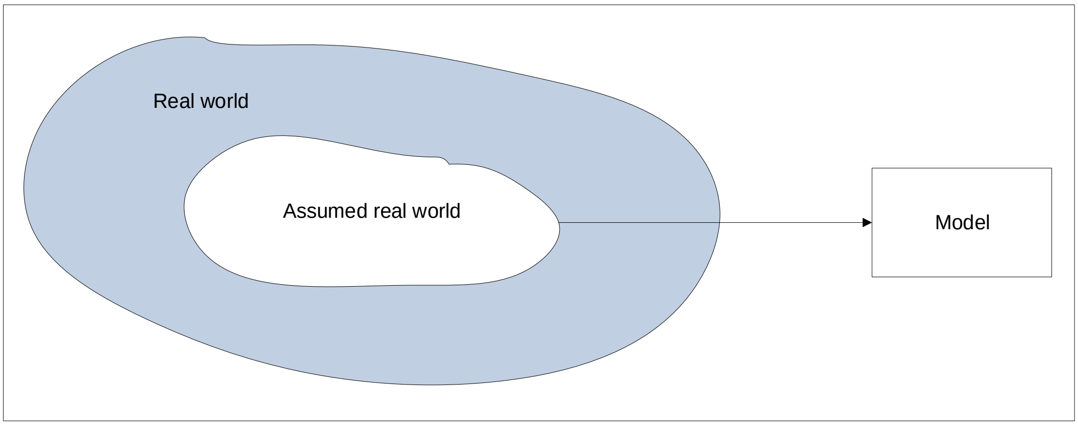


Figure B1 Levels of abstraction in model development (Taha, 2003)

The quality of the model's proposed solution depends on the accuracy of the model in representing the real system. The optimum solution of a model is best only for that model (Hillier and Lieberman, 2010). If the model happens to represent the real system reasonably well, then its solution is expected to be optimal for the real situation as well (Taha, 2003). This makes the next step, step six – validation of the model, very important. Since the model is necessarily an idealised, rather than an exact representation of the real problem, there cannot be any utopian guarantee that the optimal solution for the model will prove to be the best possible solution that could have been implemented for the real problem (Hillier and Lieberman, 2010). There are too many imponderables and uncertainties associated with real problems. However, if the model is well formulated and tested, the resulting solution should tend to be a good approximation to an ideal course of action for the real problem (Hillier and Lieberman, 2010) and provide satisfactory decision support. Validation is the process of determining the degree to which the model corresponds to the real system, or at least accurately represents the model specification. Hillier and Lieberman (2010) suggest that the test of the practical success of an operations research study should hinge on whether it provides a better guide for action than can be obtained by any other means. To complete the validation process, it must be argued that conclusions drawn from the model are meaningful enough to infer decisions for the person(s) with the problem (Rardin, 1998).

Once steps five and six have been completed and confidence in validity and robustness of the model solutions is high, a suitable alternative needs to be selected out of the options generated (step seven) – i.e. a decision needs to be made on which solution to implement. When there are multiple optimal solutions, stakeholder involvement and the use of additional decision tools, such as multi-criteria decision-making, should be encouraged. Though the solution of the mathematical model provides a basis for making a decision, intangible (unquantifiable) factors (such as human behaviour) must be accounted for before a final decision can be reached (Taha, 2003). Model-based analysis needs to be used as a contribution to strategy formulation, rather than being seen as the whole process (May *et al.*, 2005).

Stage 4: The post-decision stage

The final stage of the operations research process is the post-decision stage. This stage consists of three steps: step eight – developing a decision support system; step nine – development of an implementation strategy and implementation of the solution chosen in step seven; and step ten – monitoring of the implemented solution.

A methodology should be in place to instruct on the presentation of the methodology, results and conclusions of the study to decision-makers (Winston, 2004). Good communication at the appropriate level of technicality is key in this design. Model assumptions need to be made clear and results need to be able to be presented in a user-friendly way to decision-makers and to stakeholders as part of the participation process (May *et al.*, 2005). This also involves the translation of the results into operating instructions issued in understandable form to the individuals who will administer the recommended system (Taha, 2003). A decision support system can be developed and deployed to allow repeated use of the model by an array of decision-makers going forward (Hillier and Lieberman, 2010). The standard operations research process is an iterative process, where feedback from step ten feeds into step one and adjustments are made as needed throughout, when the process is repeated.

Appendix C - Measure Correlation Matrix

A correlation matrix between the various measure settings in the case study model solution set is shown in Table C1.

Table C1 Correlation matrix between freight energy management measures in the case study

Measure	GM1	GM2	GM3	GM4	GM5	GM6a: Road	GM6a: Rail	GM6a: Air	GM6a: Water	GM6a: Hyperloop	GM6b: Road	GM6b: Rail	GM6b: Air	GM6b: Water	GM6b: Hyperloop
GM1		0.098484848	0.024140227	0.184637236	0.251259454	0.355510055	0.168636704	N/A	0.094962384	0.51508188	0.25646625	0.014851419	N/A	0.035387227	0.032549318
GM2			0.41843061	0.492365964	0.100503782	0.025010758	0.591112305	N/A	0.083885901	0.134005042	0.122565363	0.515749277	N/A	0.228620112	0.333383919
GM3				0.196116135	0.053376051	0.074004385	0.111903592	N/A	0.392640885	0.042997375	0.332423903	0.123329722	N/A	0.037834536	0.174959872
GM4					1.13312E-17	0.078787322	0.482519619	N/A	0.296353156	0.045360921	0.110796069	0.208401497	N/A	0.07943725	0.044071984
GM5						0.343655381	0.053937138	N/A	0.104821592	0.351851852	0.260820049	0.26688113	N/A	0.199213604	0.071969249
GM6a: Road							0.147230291	N/A	0.509724819	0.206719904	0.291701481	0.243880332	N/A	0.120012324	0.287022439
GM6a: Rail								N/A	0.392653759	0.120251156	0.54393626	0.466875551	N/A	0.6023508	0.6503038
GM6a: Air									N/A	N/A	N/A	N/A	N/A	N/A	N/A
GM6a: Water										0.195002993	0.693944515	0.181030605	N/A	0.65986945	0.766308307
GM6a: Hyperloop											0.046537712	0.276512623	N/A	0.146107135	0.05161431
GM6b: Road												0.276512623	N/A	0.704476931	0.572516204
GM6b: Rail													N/A	0.606678941	0.266838761
GM6b: Air														N/A	N/A
GM6b: Water															0.662090122
GM6b: Hyperloop															
LM1															
LM2															
LM3: Road															
LM3: Rail															
LM3: Air															
LM3: Water															
LM3: Hyperloop															
LM4															
LM5: Road 1															
LM5: Road 2															
LM5: Road 3															
LM5: Road 4															
LM5: Road 5															
LM5: Rail															
LM5: Air 1															
LM5: Air 2															
LM5: Water															
LM5: Hyperloop															
LM6: Mean															
LM6: Standard deviation															
LM7: Road 1															
LM7: Road 2															
LM7: Rail 5															
LM7: Rail 6															
LM7: Rail 7															
LM7: Air															
LM7: Water															
LM7: Hyperloop															
LM8: Diesel															
LM8: Biodiesel															
LM8: Conventional electricity															
LM8: Jet fuel															
LM8: Bunker fuel															
LM8: Solar electricity															

Measure	LM1	LM2	LM3: Road	LM3: Rail	LM3: Air	LM3: Water	LM3: Hyperloop	LM4	LM5: Road 1	LM5: Road 2	LM5: Road 3	LM5: Road 4	LM5: Road 5	LM5: Rail	LM5: Air 1
GM1	0.243359016	0.434603565	0.137023938	0.088118535	0.053017443	0.120485067	0.105912567	0.209080787	0.11490437	0.232008566	0.187598826	0.225675259	0.014531014	N/A	0.113392271
GM2	0.154847879	0.043245487	0.113854783	0.146900635	0.026425472	0.193150619	0.066904362	0.200388787	0.997913033	0.805075071	0.927485187	0.828841882	0.913868432	N/A	0.011590698
GM3	0.143516487	0.029005517	0.246364957	0.210017816	0.099785596	0.031844067	0.14806531	0.051460896	0.417557359	0.336868053	0.388088192	0.346812814	0.382390525	N/A	0.013070574
GM4	0.099701848	0.124397067	0.208122704	0.188612513	0.118977182	0.269871471	0.241893787	0.316891052	0.491338412	0.396391563	0.456662138	0.408093532	0.449957711	N/A	0.137146382
GM5	0.324962838	0.503083095	0.291884744	0.062126645	0.218662396	0.112112296	0.665689994	0.309215822	0.100294033	0.080913089	0.093215769	0.083301743	0.091847233	N/A	0.146947266
GM6a: Road	0.050325754	0.094995832	0.539208512	0.235982249	0.445215475	0.033175749	0.038792415	0.457822664	0.111426369	0.001300819	0.050666094	0.007290384	0.18043883	N/A	0.024015582
GM6a: Rail	0.272892232	0.012749247	0.008157701	0.052494064	0.092303893	0.314958891	0.002397107	0.091862189	0.520598662	0.469651805	0.512658584	0.478817819	0.434067788	N/A	0.199339042
GM6a: Air	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
GM6a: Water	0.267686102	0.000366129	0.314985187	0.065732724	0.268295645	0.263638724	0.057003178	0.320991774	0.237339276	0.268535159	0.265286338	0.269170648	0.151105299	N/A	0.198810139
GM6a: Hyperloop	0.053786278	0.030581756	0.501922723	0.030264906	0.636819197	0.375456472	0.054052873	0.607953393	0.332688158	0.268399082	0.309208646	0.276322555	0.304669039	N/A	0.105436008
GM6b: Road	0.113131094	0.197111715	0.377733027	0.026175901	0.477398862	0.328238283	0.298982235	0.37116708	0.007525164	0.278266019	0.164876844	0.260723495	0.227104148	N/A	0.209979501
GM6b: Rail	0.014337275	0.015271257	0.406107876	0.12677279	0.375181302	0.117177127	0.147287835	0.522148558	0.589878673	0.475889781	0.548247907	0.489938636	0.540198876	N/A	0.077657474
GM6b: Air	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
GM6b: Water	0.04841856	0.047902002	0.449523828	0.052437465	0.522514646	0.146072042	0.113175039	0.366354824	0.070746873	0.051554908	0.002744322	0.042797375	0.158174044	N/A	0.12307077
GM6b: Hyperloop	0.609701495	0.470838852	0.2450835	0.287576435	0.032397454	0.099681905	0.109695508	0.143226839	0.133725378	0.107884119	0.124287692	0.111068991	0.122462978	N/A	0.375091042
LM1		0.703272636	0.189832126	0.498942746	0.251837503	0.371963752	0.174493687	0.067826708	0.166249062	0.232366188	0.211500612	0.229929354	0.067791536	N/A	0.815860093
LM2			0.083939786	0.247647136	0.106494119	0.111601684	0.2935664	0.111974331	0.054739485	0.141230943	0.107179924	0.13621477	0.03331749	N/A	0.595199328
LM3: Road				0.580826199	0.761283913	0.291808006	0.099760993	0.87234192	0.10825133	0.042370022	0.074531526	0.047875568	0.137787045	N/A	0.177285401
LM3: Rail					0.039026177	0.113526613	0.107315079	0.316788491	0.144744931	0.101279614	0.125542106	0.105735739	0.145874591	N/A	0.561126521
LM3: Air						0.485129514	0.005615909	0.802403353	0.032664371	0.079092786	0.06095045	0.076436971	0.01542562	N/A	0.28552497
LM3: Water							0.24662582	0.318283934	0.200273393	0.224634824	0.222717565	0.225298839	0.129193892	N/A	0.301988328
LM3: Hyperloop								0.199751174	0.066764734	0.053863034	0.062052804	0.055453137	0.061141784	N/A	0.08124427
LM4									0.200828294	0.169207122	0.190823606	0.173522221	0.177735957	N/A	0.015125746
LM5: Road 1										0.84169743	0.94969054	0.8632392	0.885744201	N/A	0.00960452
LM5: Road 2											0.968458779	0.999150061	0.494898281	N/A	0.185149635
LM5: Road 3												0.977906798	0.695808405	N/A	0.111825612
LM5: Road 4													0.530296518	N/A	0.173828362
LM5: Road 5														N/A	0.143709246
LM5: Rail															N/A
LM5: Air 1															
LM5: Air 2															
LM5: Water															
LM5: Hyperloop															
LM6: Mean															
LM6: Standard deviation															
LM7: Road 1															
LM7: Road 2															
LM7: Rail 5															
LM7: Rail 6															
LM7: Rail 7															
LM7: Air															
LM7: Water															
LM7: Hyperloop															
LM8: Diesel															
LM8: Biodiesel															
LM8: Conventional electricity															
LM8: Jet fuel															
LM8: Bunker fuel															
LM8: Solar electricity															

Measure	LM5: Air 2	LM5: Water	LM5: Hyperloop	LM6: Mean	LM6: Standard deviation	LM7: Road 1	LM7: Road 2	LM7: Rail 5	LM7: Rail 6	LM7: Rail 7	LM7: Air	LM7: Water	LM7: Hyperloop	LM8: Diesel	LM8: Biodiesel
GM1	0.113392271	0.029636948	0.251259454	0.255516933	0.159298597	0.055398839	0.055398839	0.019855357	0.196820206	0.204081441	N/A	0.029636948	0.251259454	0.057338503	0.130110747
GM2	0.011590698	0.081501608	0.100503782	0.111187285	0.081501608	0.986745196	0.986745196	0.136917714	0.160358088	0.289245896	N/A	0.081501608	0.100503782	0.456747451	0.992045636
GM3	0.013070574	0.149527519	0.053376051	0.305469672	0.011804804	0.412884394	0.412884394	0.01014605	0.09964695	0.082751463	N/A	0.149527519	0.053376051	0.174301667	0.41510226
GM4	0.137146382	0.240771706	1.13312E-17	0.442959406	0.240771706	0.48583975	0.48583975	0.266910991	0.048954646	0.317573925	N/A	0.240771706	1.13312E-17	0.439123135	0.488449506
GM5	0.146947266	0.221162934	1	0.134741607	0.221162934	0.099171624	0.099171624	0.046043078	0.23295359	0.264506993	N/A	0.221162934	1	0.066684379	0.099704338
GM6a: Road	0.024015582	0.198168721	0.260820049	0.06558752	0.16785445	0.148291481	0.148291481	0.096855809	0.220284139	0.107132442	N/A	0.198168721	0.260820049	0.019666847	0.100374456
GM6a: Rail	0.199339042	0.261449537	0.26688113	0.140613605	0.076586228	0.494021089	0.494021089	0.083242323	0.003378941	0.081624066	N/A	0.261449537	0.26688113	0.334780145	0.523198592
GM6a: Air	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
GM6a: Water	0.198810139	0.16598846	0.199213604	0.21013922	0.094265051	0.202478507	0.202478507	0.087047192	0.048530516	0.043320991	N/A	0.16598846	0.199213604	0.149500507	0.244729046
GM6a: Hyperloop	0.105436008	0.471719933	0.071969249	0.031875657	0.404193563	0.32896498	0.32896498	0.162642987	0.064955332	0.104970456	N/A	0.471719933	0.071969249	0.16063805	0.330732062
GM6b: Road	0.209979501	0.407100988	0.343655381	0.088743631	0.407100988	0.106314451	0.106314451	0.049934769	0.048039781	0.09573374	N/A	0.407100988	0.343655381	0.16019076	0.038512739
GM6b: Rail	0.077657474	0.185330091	0.053937138	0.054082745	0.088515864	0.583277228	0.583277228	0.240083314	0.058519193	0.299185221	N/A	0.185330091	0.053937138	0.429898202	0.586410383
GM6b: Air	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
GM6b: Water	0.12307077	0.279636212	0.104821592	0.261898739	0.259414586	0.11535388	0.11535388	0.08884185	0.126882823	0.028043837	N/A	0.279636212	0.104821592	0.118203569	0.057946387
GM6b: Hyperloop	0.375091042	0.036860489	0.351851852	0.245844336	0.154267973	0.132228831	0.132228831	0.105052672	0.248064066	0.338722402	N/A	0.036860489	0.351851852	0.379926758	0.132939117
LM1	0.815860093	0.310140919	0.324962838	0.378941978	0.182485223	0.12333082	0.12333082	0.125572545	0.288753569	0.397631463	N/A	0.310140919	0.324962838	0.419099038	0.176471882
LM2	0.595199328	0.015583997	0.503083095	0.042665191	0.141714324	0.013559771	0.013559771	0.244557568	0.392460761	0.615692983	N/A	0.015583997	0.503083095	0.244011976	0.065484111
LM3: Road	0.177285401	0.547892755	0.291884744	0.163194037	0.536799555	0.125830617	0.125830617	0.175490514	0.075568613	0.10814101	N/A	0.547892755	0.291884744	0.453373149	0.10248884
LM3: Rail	0.561126521	0.273477302	0.062126645	0.040637917	0.291144123	0.149600557	0.149600557	0.033462282	0.090036908	0.1181884	N/A	0.273477302	0.062126645	0.714256651	0.142127402
LM3: Air	0.28552497	0.626477206	0.218662396	0.236533212	0.577433765	0.010257567	0.010257567	0.144065298	0.155146527	0.001797564	N/A	0.626477206	0.218662396	0.027023267	0.038485042
LM3: Water	0.301988328	0.918888505	0.112112296	0.264238652	0.803061846	0.17167709	0.17167709	0.051629386	0.0456829	0.00990882	N/A	0.918888505	0.112112296	0.103192241	0.206285346
LM3: Hyperloop	0.08124427	0.119942973	0.665689994	0.243899639	0.119942973	0.066017557	0.066017557	0.160263506	0.074827571	0.23312492	N/A	0.119942973	0.665689994	0.12123939	0.06637218
LM4	0.015125746	0.538487791	0.309215822	0.329475393	0.521027873	0.195577146	0.195577146	0.169219302	0.098478867	0.080352349	N/A	0.538487791	0.309215822	0.41132547	0.200466866
LM5: Road 1	0.00960452	0.097591143	0.100294033	0.101570574	0.097591143	0.974207279	0.974207279	0.113272359	0.155394951	0.260527311	N/A	0.097591143	0.100294033	0.443907142	0.998103546
LM5: Road 2	0.185149635	0.214978869	0.080913089	0.003304816	0.214978869	0.698145465	0.698145465	0.104356718	0.086582266	0.025404402	N/A	0.214978869	0.080913089	0.258518948	0.873339069
LM5: Road 3	0.111825612	0.169731356	0.093215769	0.048789311	0.169731356	0.854522582	0.854522582	0.008258101	0.121931854	0.105491695	N/A	0.169731356	0.093215769	0.35480273	0.967168644
LM5: Road 4	0.173828362	0.208432585	0.083301743	0.01084375	0.208432585	0.727064376	0.727064376	0.088914947	0.092808333	0.003861227	N/A	0.208432585	0.083301743	0.275576364	0.892675973
LM5: Road 5	0.143709246	0.027753747	0.091847233	0.160618426	0.027753747	0.96764156	0.96764156	0.272002787	0.175648611	0.441110717	N/A	0.027753747	0.091847233	0.492149427	0.855491108
LM5: Rail	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
LM5: Air 1	1	0.285734789	0.146947266	0.148458962	0.207692871	0.06464221	0.06464221	0.239727593	0.259166317	0.486257027	N/A	0.285734789	0.146947266	0.553353428	0.029772809
LM5: Air 2		0.285734789	0.146947266	0.148458962	0.207692871	0.06464221	0.06464221	0.239727593	0.259166317	0.486257027	N/A	0.285734789	0.146947266	0.553353428	0.029772809
LM5: Water			0.221162934	0.21644101	0.873188406	0.039559075	0.039559075	0.049082001	0.036034098	0.08365013	N/A	1	0.221162934	0.158638596	0.112550219
LM5: Hyperloop				0.134741607	0.221162934	0.099171624	0.099171624	0.046043078	0.23295359	0.264506993	N/A	0.221162934	1	0.066684379	0.099704338
LM6: Mean					0.253037316	0.133298227	0.133298227	0.018657956	0.21459526	0.219466445	N/A	0.21644101	0.134741607	0.063558759	0.092008167
LM6: Standard deviation						0.039559075	0.039559075	0.018763828	0.025028022	0.004269325	N/A	0.873188406	0.221162934	0.200390837	0.112550219
LM7: Road 1							1	0.193808195	0.169864444	0.356067957	N/A	0.039559075	0.099171624	0.480566933	0.958469007
LM7: Road 2								0.193808195	0.169864444	0.356067957	N/A	0.039559075	0.099171624	0.480566933	0.958469007
LM7: Rail 5									0.47820128	0.571767517	N/A	0.049082001	0.046043078	0.258162545	0.090290833
LM7: Rail 6										0.447110343	N/A	0.036034098	0.23295359	0.153816849	0.150059682
LM7: Rail 7											N/A	0.08365013	0.264506993	0.406620635	0.232137196
LM7: Air												N/A	N/A	N/A	N/A
LM7: Water													0.221162934	0.158638596	0.112550219
LM7: Hyperloop														0.066684379	0.099704338
LM8: Diesel															0.429941335
LM8: Biodiesel															
LM8: Conventional electricity															
LM8: Jet fuel															
LM8: Bunker fuel															
LM8: Solar electricity															

Measure	LM8: Conventional electricity	LM8: Jet fuel	LM8: Bunker fuel	LM8: Solar electricity	Empty tkm
GM1	0.111482311	0.055918315	0.214611145	0.104237972	0.244600141
GM2	0.42029659	0.112122739	0.096534333	0.41543655	0.100580286
GM3	0.035247179	0.087681096	0.190727183	0.06112597	0.29581885
GM4	0.398499876	0.157112854	0.242069035	0.386741509	0.126348737
GM5	0.241881913	0.223810044	0.189552598	0.148710401	0.067886834
GM6a: Road	0.296389161	0.388314419	0.207425667	0.29922556	0.053198328
GM6a: Rail	0.256620813	0.084496269	0.365949806	0.256821574	0.31864564
GM6a: Air	N/A	N/A	N/A	N/A	N/A
GM6a: Water	0.335711782	0.230496737	0.368684542	0.336259751	0.269219891
GM6a: Hyperloop	0.573986489	0.648896725	0.028252095	0.535870097	0.067771481
GM6b: Road	0.182796189	0.437559672	0.31703283	0.133257397	0.237893375
GM6b: Rail	0.627779215	0.398192069	0.108328502	0.591143622	0.028715171
GM6b: Air	N/A	N/A	N/A	N/A	N/A
GM6b: Water	0.266418903	0.481474588	0.157423234	0.246032226	0.111539464
GM6b: Hyperloop	0.296930603	0.01302235	0.204204261	0.296431563	0.347442779
LM1	0.139501332	0.276524406	0.345929606	0.154932351	0.626726403
LM2	0.038467091	0.136943479	0.348315524	0.005852571	0.296641303
LM3: Road	0.81310612	0.732142009	0.212322498	0.800131886	0.047308402
LM3: Rail	0.438821251	0.034801406	0.330802891	0.525604248	0.246478299
LM3: Air	0.668915242	0.980963055	0.113583248	0.610619612	0.302776317
LM3: Water	0.311582086	0.549602239	0.63268961	0.324748811	0.392639473
LM3: Hyperloop	0.008284427	0.028108147	0.107829395	0.124670418	0.096505098
LM4	0.847047754	0.784592618	0.143375591	0.811694839	0.294131031
LM5: Road 1	0.418377593	0.12071294	0.098669805	0.414569548	0.098738076
LM5: Road 2	0.328799662	0.171327949	0.099184915	0.33445761	0.065980048
LM5: Road 3	0.383786758	0.155082433	0.103064533	0.385311247	0.083836038
LM5: Road 4	0.339332349	0.169388802	0.100259952	0.344331212	0.06922216
LM5: Road 5	0.390646627	0.046981607	0.073525749	0.379654349	0.10218056
LM5: Rail	N/A	N/A	N/A	N/A	N/A
LM5: Air 1	0.217438097	0.280155315	0.340770139	0.253607559	0.502903747
LM5: Air 2	0.217438097	0.280155315	0.340770139	0.253607559	0.502903747
LM5: Water	0.48523448	0.687688387	0.392594292	0.484213662	0.322875105
LM5: Hyperloop	0.241881913	0.223810044	0.189552598	0.148710401	0.067886834
LM6: Mean	0.162842067	0.210456211	0.363388783	0.136675304	0.607799085
LM6: Standard deviation	0.454899323	0.598161138	0.368981188	0.457170853	0.325430566
LM7: Road 1	0.41734393	0.088460385	0.08938181	0.40993002	0.103349271
LM7: Road 2	0.41734393	0.088460385	0.08938181	0.40993002	0.103349271
LM7: Rail 5	0.265155659	0.113338543	0.000184028	0.183902062	0.192252442
LM7: Rail 6	0.018469513	0.141534415	0.066188152	0.049832877	0.040346241
LM7: Rail 7	0.287308533	0.016781242	0.061642097	0.233851533	0.158115575
LM7: Air	N/A	N/A	N/A	N/A	N/A
LM7: Water	0.48523448	0.687688387	0.392594292	0.484213662	0.322875105
LM7: Hyperloop	0.241881913	0.223810044	0.189552598	0.148710401	0.067886834
LM8: Diesel	0.722233338	0.064588252	0.256859261	0.771810873	0.173584991
LM8: Biodiesel	0.414922387	0.128432977	0.100322143	0.412132017	0.096598185
LM8: Conventional electricity		0.70776845	0.220348879	0.982195059	0.033867818
LM8: Jet fuel			0.116402253	0.654378017	0.28275267
LM8: Bunker fuel				0.264385486	0.384906071
LM8: Solar electricity					0.027080464

Appendix D - Key Findings per Decision Variable

A summary table of the key findings per decision variable in the case study is presented in Table D1.

Table D1 Key findings per decision variable in the case study

Decision variable	Decision variable ID	Summary findings per decision variable in the case study results
Network design	GM1	Preference for network configuration one (68%)
Vehicle park restrictions	GM2	Strong preference for vehicle park two (94%)
Taxes	GM3	Weak preference for a carbon tax (26%).
Driver training	GM4	Weak preference for driver training (20%).
New technology	GM5	Weak preference for hyperloop (14%).
Overloading tolerance and enforcement	GM6	Slight bias toward higher tolerance and prevalence values.
Intermodal/unimodal routing	LM1	No clear preference.
Intramodal split	LM2	No clear preference.
Modal split	LM3	Very influential decision variable. Environmentally speaking surface freight is preferred. Socially air freight outperforms all other modes.
Route split	LM4	Preference for balancing loads over the network (57%).
Vehicle split	LM5	No clear preference.
Vehicle loading regimes	LM6	Some inferences can be made. High vehicle utilisation corresponds to good environmental performance and the converse applies for social performance.
Propulsion system split	LM7	No clear preference.
Energy source split	LM8	Strong preference environmentally for renewable energy sources.

Appendix E - Case Study Results per Decision Variable

Table E1 contains all the decision variable values for each solution included in the Pareto solution set of the case study model.

Table E1 Decision variable value outputs for each solution in the case study Pareto solution set

Origin	Number in origin output	Pareto set number	Cluster number	GM1	GM2	GM3	GM4	GM5	GM6a: Road	GM6a: Rail	GM6a: Air
INITIAL A	2	2	1	1	2	0	1	1	0.05	0.05	0
INITIAL A	8	6	1	2	2	0	0	1	0.1	0.02	0
AMOSA	23	17	1	1	2	0	0	0	0.2	0.05	0
AMOSA	28	19	1	1	2	0	0	0	0.2	0.05	0
AMOSA	32	20	1	1	2	0	0	0	0.2	0.05	0
AMOSA	40	22	1	1	2	0	0	0	0.2	0.05	0
AMOSA	43	23	1	2	2	0	0	0	0.2	0.05	0
AMOSA	45	24	1	2	2	0	0	0	0.2	0.05	0
AMOSA	46	25	1	2	2	0	0	0	0.01	0.01	0
AMOSA	47	26	1	2	2	0	0	0	0.2	0.01	0
AMOSA	48	27	1	1	2	0	0	0	0.2	0.01	0
AMOSA	49	28	1	1	2	1	0	0	0.2	0.01	0
AMOSA	50	29	1	1	2	1	0	0	0.2	0.01	0
AMOSA	51	30	1	1	2	1	0	0	0.2	0.01	0
AMOSA	52	31	1	1	2	1	0	0	0.2	0.01	0
AMOSA	54	32	1	1	2	0	0	0	0.2	0.01	0
AMOSA	55	33	1	2	2	0	0	0	0.2	0.01	0
INITIAL A	3	3	2	2	2	0	0	0	0.01	0.075	0
INITIAL A	10	8	2	2	1	1	1	0	0.01	0.1	0
INITIAL A	13	9	2	1	1	1	1	0	0.3	0.1	0
AMOSA	3	10	2	1	2	0	1	0	0.2	0.05	0
AMOSA	5	11	2	1	2	0	1	0	0.1	0.05	0
AMOSA	6	12	2	1	2	0	0	0	0.1	0.05	0
AMOSA	7	13	2	1	2	0	0	0	0.1	0.05	0
AMOSA	8	14	2	1	2	0	0	0	0.1	0.05	0
AMOSA	9	15	2	1	2	0	0	0	0.1	0.05	0
AMOSA	76	34	2	2	2	0	0	1	0.1	0.02	0
AMOSA	77	35	2	2	2	1	0	1	0.1	0.02	0
INITIAL A	1	1	3	2	2	1	0	0	0.1	0.01	0
INITIAL A	4	4	3	1	2	0	1	0	0.2	0.05	0
INITIAL A	7	5	3	1	2	0	0	1	0.1	0.075	0
INITIAL A	9	7	3	1	2	1	1	0	0.1	0.05	0
AMOSA	10	16	3	1	2	0	0	0	0.1	0.05	0
AMOSA	26	18	3	1	2	0	0	0	0.2	0.05	0
AMOSA	39	21	3	1	2	0	0	0	0.2	0.05	0

Origin	Number in origin output	Pareto set number	Cluster number	GM6a: Water	GM6a: Hyperloop	GM6b: Road	GM6b: Rail	GM6b: Air	GM6b: Water	GM6b: Hyperloop	LM1
INITIAL A	2	2	1	0.3	0.03	0.2	0.1	0	0.2	0.1	76%
INITIAL A	8	6	1	0.2	0.02	0.01	0.01	0	0.2	0.05	83%
AMOSA	23	17	1	0.1	0.03	0.2	0.15	0	0.05	0.05	99%
AMOSA	28	19	1	0.1	0.03	0.2	0.15	0	0.05	0.05	89%
AMOSA	32	20	1	0.1	0.03	0.2	0.15	0	0.05	0.05	96%
AMOSA	40	22	1	0.1	0.03	0.2	0.15	0	0.05	0.05	94%
AMOSA	43	23	1	0.1	0.03	0.2	0.15	0	0.05	0.05	96%
AMOSA	45	24	1	0.1	0.03	0.2	0.15	0	0.05	0.05	96%
AMOSA	46	25	1	0.01	0.01	0.01	0.05	0	0.2	0.1	96%
AMOSA	47	26	1	0.3	0.05	0.01	0.05	0	0.2	0.1	96%
AMOSA	48	27	1	0.3	0.05	0.01	0.05	0	0.2	0.1	22%
AMOSA	49	28	1	0.3	0.05	0.01	0.05	0	0.2	0.1	22%
AMOSA	50	29	1	0.3	0.05	0.01	0.05	0	0.2	0.1	22%
AMOSA	51	30	1	0.3	0.05	0.01	0.05	0	0.2	0.1	22%
AMOSA	52	31	1	0.3	0.05	0.01	0.05	0	0.2	0.1	22%
AMOSA	54	32	1	0.3	0.05	0.01	0.05	0	0.2	0.1	22%
AMOSA	55	33	1	0.3	0.05	0.01	0.05	0	0.2	0.1	17%
INITIAL A	3	3	2	0.01	0.03	0.2	0.01	0	0.1	0.05	16%
INITIAL A	10	8	2	0.1	0.03	0.15	0.25	0	0.01	0.01	6%
INITIAL A	13	9	2	0.3	0.03	0.01	0.2	0	0.1	0.01	63%
AMOSA	3	10	2	0.3	0.03	0.1	0.1	0	0.25	0.1	10%
AMOSA	5	11	2	0.01	0.05	0.25	0.05	0	0.1	0.01	10%
AMOSA	6	12	2	0.01	0.05	0.25	0.05	0	0.1	0.01	10%
AMOSA	7	13	2	0.01	0.05	0.25	0.05	0	0.1	0.01	10%
AMOSA	8	14	2	0.01	0.05	0.25	0.05	0	0.1	0.01	10%
AMOSA	9	15	2	0.01	0.05	0.25	0.05	0	0.1	0.01	10%
AMOSA	76	34	2	0.2	0.02	0.01	0.01	0	0.2	0.05	94%
AMOSA	77	35	2	0.2	0.02	0.01	0.01	0	0.2	0.05	94%
INITIAL A	1	1	3	0.05	0.01	0.2	0.25	0	0.01	0.05	90%
INITIAL A	4	4	3	0.3	0.03	0.1	0.1	0	0.25	0.1	89%
INITIAL A	7	5	3	0.05	0.04	0.1	0.1	0	0.01	0.01	92%
INITIAL A	9	7	3	0.3	0.05	0.25	0.01	0	0.05	0.1	98%
AMOSA	10	16	3	0.01	0.05	0.25	0.05	0	0.1	0.01	72%
AMOSA	26	18	3	0.1	0.03	0.2	0.15	0	0.05	0.05	89%
AMOSA	39	21	3	0.1	0.03	0.2	0.15	0	0.05	0.05	91%

Origin	Number in origin output	Pareto set number	Cluster number	LM2	LM3: Road	LM3: Rail	LM3: Air	LM3: Water	LM3: Hyperloop	LM4	LM5: Road 1
INITIAL A	2	2	1	76%	0.353949404	0.207496175	0.144014057	0.12082125	0.173719113	0.094260813	1
INITIAL A	8	6	1	83%	0.231571481	0.688700437	0.050021449	0	0.029706633	0.137774475	1
AMOSA	23	17	1	12%	0.255191596	0.532966404	0.106559426	0.105282575	0	0.251678061	1
AMOSA	28	19	1	3%	0.062514968	0.542379482	0.269864596	0.125240954	0	0.073720153	1
AMOSA	32	20	1	9%	0.087878503	0.534736313	0.230167943	0.147217241	0	0.107138062	1
AMOSA	40	22	1	81%	0.667618663	0.216754473	0.03679242	0.078834444	0	1	1
AMOSA	43	23	1	83%	0.656130867	0.23764419	0.028684065	0.077540878	0	0.941467405	1
AMOSA	45	24	1	83%	0.648070993	0.249886572	0.024671924	0.077370511	0	0.941467405	1
AMOSA	46	25	1	83%	0.630908168	0.272546714	0.023342777	0.073202341	0	0.941467405	1
AMOSA	47	26	1	83%	0.607215507	0.296674126	0.023237662	0.072872705	0	0.941467405	1
AMOSA	48	27	1	8%	0.683175807	0.178161992	0.040451732	0.098210469	0	0.750817911	1
AMOSA	49	28	1	8%	0.708888006	0.184984839	0.030960328	0.075166827	0	0.750817911	1
AMOSA	50	29	1	8%	0.705093877	0.174701718	0.035067065	0.08513734	0	0.750817911	1
AMOSA	51	30	1	8%	0.737279036	0.175094316	0.025563201	0.062063447	0	0.750817911	1
AMOSA	52	31	1	8%	0.724157046	0.15949329	0.033942527	0.082407137	0	0.750817911	1
AMOSA	54	32	1	8%	0.712672267	0.170686412	0.034027611	0.08261371	0	0.750817911	1
AMOSA	55	33	1	4%	0.707828869	0.17261327	0.031008028	0.088549832	0	0.68669879	1
INITIAL A	3	3	2	16%	0.235749665	0.204680454	0.473518075	0.086051807	0	0.220477727	1
INITIAL A	10	8	2	6%	0.369084327	0.245040335	0.385875338	0	0	0.022247101	13%
INITIAL A	13	9	2	63%	0.55708293	0.203086567	0.193966931	0.045863571	0	0.063097252	23%
AMOSA	3	10	2	10%	0.107200145	0.279958976	0.612840879	0	0	0	1
AMOSA	5	11	2	10%	0.106320141	0.277796548	0.615883311	0	0	0	1
AMOSA	6	12	2	10%	0.0992862	0.323390379	0.577323421	0	0	0	1
AMOSA	7	13	2	10%	0.105323646	0.276093214	0.618583141	0	0	0	1
AMOSA	8	14	2	10%	0.114649867	0.255976915	0.629373218	0	0	0	1
AMOSA	9	15	2	10%	0.110526356	0.281929747	0.607543898	0	0	0	1
AMOSA	76	34	2	94%	0.033323211	0.336120451	0.624538834	0	0.006017504	0.034823259	1
AMOSA	77	35	2	94%	0.045277077	0.331964006	0.616815826	0	0.005943091	0.034823259	1
INITIAL A	1	1	3	90%	0.155157576	0.327487426	0.426850308	0.090504691	0	0.106621748	1
INITIAL A	4	4	3	89%	0.025384819	0.956307044	0.018308137	0	0	0.446601424	1
INITIAL A	7	5	3	92%	0.059359883	0.211713795	0.518121118	0.113764741	0.097040463	0.015633916	1
INITIAL A	9	7	3	98%	0.059284385	0.592556207	0.27371229	0.074447119	0	0.136163629	1
AMOSA	10	16	3	72%	0.247079365	0.484908489	0.268012146	0	0	0.137859447	1
AMOSA	26	18	3	3%	0.061333967	0.531772775	0.284877675	0.122015583	0	0.073720153	1
AMOSA	39	21	3	4%	0.159373097	0.383001064	0.348633857	0.108991982	0	0.051479077	1

Origin	Number in origin output	Pareto set number	Cluster number	LM5: Road 2	LM5: Road 3	LM5: Road 4	LM5: Road 5	LM5: Rail	LM5: Air 1	LM5: Air 2	LM5: Water
INITIAL A	2	2	1	0	0	0	0	1	0.580161086	0.419838914	1
INITIAL A	8	6	1	0	0	0	0	1	0.501574398	0.498425602	0
AMOSA	23	17	1	0	0	0	0	1	0.495883902	0.504116098	1
AMOSA	28	19	1	0	0	0	0	1	0.327685003	0.672314997	1
AMOSA	32	20	1	0	0	0	0	1	0.36286932	0.63713068	1
AMOSA	40	22	1	0	0	0	0	1	0.655738454	0.344261546	1
AMOSA	43	23	1	0	0	0	0	1	0.488940402	0.511059598	1
AMOSA	45	24	1	0	0	0	0	1	0.419522271	0.580477729	1
AMOSA	46	25	1	0	0	0	0	1	0.419522271	0.580477729	1
AMOSA	47	26	1	0	0	0	0	1	0.419522271	0.580477729	1
AMOSA	48	27	1	0	0	0	0	1	0.806719395	0.193280605	1
AMOSA	49	28	1	0	0	0	0	1	0.806719395	0.193280605	1
AMOSA	50	29	1	0	0	0	0	1	0.806719395	0.193280605	1
AMOSA	51	30	1	0	0	0	0	1	0.806719395	0.193280605	1
AMOSA	52	31	1	0	0	0	0	1	0.792231149	0.207768851	1
AMOSA	54	32	1	0	0	0	0	1	0.792231149	0.207768851	1
AMOSA	55	33	1	0	0	0	0	1	0.670983197	0.329016803	1
INITIAL A	3	3	2	0	0	0	0	1	0.953945845	0.046054155	1
INITIAL A	10	8	2	15%	4%	42%	25%	1	0.898773054	0.101226946	0
INITIAL A	13	9	2	3%	2%	9%	64%	1	0.32152984	0.67847016	1
AMOSA	3	10	2	0	0	0	0	1	0.826616283	0.173383717	0
AMOSA	5	11	2	0	0	0	0	1	0.826616283	0.173383717	0
AMOSA	6	12	2	0	0	0	0	1	0.826616283	0.173383717	0
AMOSA	7	13	2	0	0	0	0	1	0.826616283	0.173383717	0
AMOSA	8	14	2	0	0	0	0	1	0.826616283	0.173383717	0
AMOSA	9	15	2	0	0	0	0	1	0.826616283	0.173383717	0
AMOSA	76	34	2	0	0	0	0	1	0.55318915	0.44681085	0
AMOSA	77	35	2	0	0	0	0	1	0.55318915	0.44681085	0
INITIAL A	1	1	3	0	0	0	0	1	0.553783596	0.446216404	1
INITIAL A	4	4	3	0	0	0	0	1	0.399734392	0.600265608	0
INITIAL A	7	5	3	0	0	0	0	1	0.533458647	0.466541353	1
INITIAL A	9	7	3	0	0	0	0	1	0.082940099	0.917059901	1
AMOSA	10	16	3	0	0	0	0	1	0.573471928	0.426528072	0
AMOSA	26	18	3	0	0	0	0	1	0.327685003	0.672314997	1
AMOSA	39	21	3	0	0	0	0	1	0.836923411	0.163076589	1

Origin	Number in origin output	Pareto set number	Cluster number	LM5: Hyperloop	LM6: Mean	LM6: Standard deviation	LM7: Road 1	LM7: Road 2	LM7: Rail 5	LM7: Rail 6	LM7: Rail 7
INITIAL A	2	2	1	1	1	2	1	0	0.208462923	0.337429761	0.454107316
INITIAL A	8	6	1	1	3	1	1	0	0.506569325	0.193086281	0.300344393
AMOSA	23	17	1	0	3	2	1	0	0.735257608	0.114551071	0.150191321
AMOSA	28	19	1	0	5	2	1	0	0.203649252	0.658944925	0.137405823
AMOSA	32	20	1	0	5	2	1	0	0.238876695	0.214559499	0.546563806
AMOSA	40	22	1	0	5	2	1	0	0.452113905	0.252192343	0.295693752
AMOSA	43	23	1	0	5	2	1	0	0.380994134	0.23580989	0.383195976
AMOSA	45	24	1	0	5	2	1	0	0.261237175	0.34086319	0.397899635
AMOSA	46	25	1	0	5	2	1	0	0.307812661	0.169543565	0.522643774
AMOSA	47	26	1	0	5	2	1	0	0.280256573	0.311600468	0.408142959
AMOSA	48	27	1	0	5	2	1	0	0.241535375	0.60850691	0.149957715
AMOSA	49	28	1	0	5	2	1	0	0.241535375	0.60850691	0.149957715
AMOSA	50	29	1	0	1	2	1	0	0.487362573	0.332831135	0.179806292
AMOSA	51	30	1	0	1	2	1	0	0.487362573	0.332831135	0.179806292
AMOSA	52	31	1	0	1	2	1	0	0.476046287	0.122596299	0.401357413
AMOSA	54	32	1	0	1	2	1	0	0.581290486	0.066012824	0.35269669
AMOSA	55	33	1	0	1	2	1	0	0.411243027	0.345526829	0.243230144
INITIAL A	3	3	2	0	3	2	1	0	0.178172364	0.334986103	0.486841533
INITIAL A	10	8	2	0	3	1	0.512406515	0.487593485	0.491569948	0.263107457	0.245322595
INITIAL A	13	9	2	0	1	2	0.327085944	0.672914056	0.015751098	0.176634996	0.807613906
AMOSA	3	10	2	0	1	1	1	0	0.436434859	0.355349679	0.208215461
AMOSA	5	11	2	0	1	1	1	0	0.083170586	0.555698181	0.361131233
AMOSA	6	12	2	0	1	1	1	0	0.083170586	0.555698181	0.361131233
AMOSA	7	13	2	0	2	2	1	0	0.388903441	0.387902946	0.223193613
AMOSA	8	14	2	0	3	1	1	0	0.669369803	0.205725366	0.124904831
AMOSA	9	15	2	0	3	1	1	0	0.406216107	0.321306896	0.272476997
AMOSA	76	34	2	1	3	1	1	0	0.335873171	0.217277546	0.446849282
AMOSA	77	35	2	1	3	1	1	0	0.335873171	0.217277546	0.446849282
INITIAL A	1	1	3	0	1	1	1	0	0.21170873	0.361538176	0.426753093
INITIAL A	4	4	3	0	1	1	1	0	0.217788786	0.22048335	0.561727864
INITIAL A	7	5	3	1	1	2	1	0	0.230037434	0.192509311	0.577453256
INITIAL A	9	7	3	0	1	2	1	0	0.34703	0.189029701	0.463940298
AMOSA	10	16	3	0	3	1	1	0	0.266369513	0.358930451	0.374700036
AMOSA	26	18	3	0	3	2	1	0	0.326415058	0.407768944	0.265815998
AMOSA	39	21	3	0	5	2	1	0	0.412807704	0.41616376	0.171028536

Origin	Number in origin output	Pareto set number	Cluster number	LM7: Air	LM7: Water	LM7: Hyperloop	LM8: Diesel	LM8: Biodiesel	LM8: Conventional electricity	LM8: Jet fuel	LM8: Bunker fuel	LM8: Solar electricity	Empty tkm
INITIAL A	2	2	1	1	1	1	0.060323025	0	0.001185999	0.065349229	0.004892679	0.868249068	40%
INITIAL A	8	6	1	1	0	1	0.318600302	0	0.096290901	0.024828395	0	0.560280402	46%
AMOSA	23	17	1	1	1	0	0.233644006	0	0.178210072	0.068604344	0.117691229	0.401850348	47%
AMOSA	28	19	1	1	1	0	0.432735289	0	0.025390434	0.227014822	0.133085951	0.181773504	33%
AMOSA	32	20	1	1	1	0	0.350611888	0	0.037008652	0.186811702	0.238139622	0.187428136	33%
AMOSA	40	22	1	1	1	0	0.040189064	0	0.003627718	0.00877059	0.008029809	0.93938282	38%
AMOSA	43	23	1	1	1	0	0.066675256	0	0.011263612	0.0067447	0.014403849	0.900912583	37%
AMOSA	45	24	1	1	1	0	0.07325077	0	0.004688098	0.0067447	0.014403849	0.900912583	40%
AMOSA	46	25	1	1	1	0	0.072581042	0	0.005357826	0.0067447	0.014403849	0.900912583	42%
AMOSA	47	26	1	1	1	0	0.070754966	0	0.007183903	0.0067447	0.014403849	0.900912583	42%
AMOSA	48	27	1	1	1	0	0.070365453	0	0	0.005840079	0.015976765	0.907817702	38%
AMOSA	49	28	1	1	1	0	0.070365453	0	0	0.005840079	0.015976765	0.907817702	51%
AMOSA	50	29	1	1	1	0	0.055123903	0	0.01524155	0.005840079	0.015976765	0.907817702	40%
AMOSA	51	30	1	1	1	0	0.04369274	0	0.026672713	0.005840079	0.015976765	0.907817702	55%
AMOSA	52	31	1	1	1	0	0.050192813	0	0.02017264	0.005840079	0.015976765	0.907817702	41%
AMOSA	54	32	1	1	1	0	0.034054701	0	0.036310752	0.005840079	0.015976765	0.907817702	41%
AMOSA	55	33	1	1	1	0	0.031986983	0	0.006025486	0.00509573	0.017844979	0.939046823	42%
INITIAL A	3	3	2	1	1	0	0.111226004	0	0	0.27409613	0.03078349	0.583894375	37%
INITIAL A	10	8	2	1	0	0	0.405501031	0.135246454	0.041877283	0.417375232	0	0	20%
INITIAL A	13	9	2	1	1	0	0.698660159	0.105575	0	0.180441583	0.015323258	0	23%
AMOSA	3	10	2	1	0	0	0.07812464	0	0.00065285	0.517756036	0	0.403466474	25%
AMOSA	5	11	2	1	0	0	0.07877749	0	0	0.517756036	0	0.403466474	24%
AMOSA	6	12	2	1	0	0	0.07877749	0	0	0.517756036	0	0.403466474	22%
AMOSA	7	13	2	1	0	0	0.07877749	0	0	0.517756036	0	0.403466474	25%
AMOSA	8	14	2	1	0	0	0.07877749	0	0	0.517756036	0	0.403466474	26%
AMOSA	9	15	2	1	0	0	0.074603062	0	0.004174429	0.517756036	0	0.403466474	25%
AMOSA	76	34	2	1	0	1	0.324837853	0	0.014784593	0.551805029	0	0.108572525	40%
AMOSA	77	35	2	1	0	1	0.324837853	0	0.014784593	0.551805029	0	0.108572525	41%
INITIAL A	1	1	3	1	1	0	0.210803408	0	0.013271849	0.209537799	0.019852216	0.546534727	40%
INITIAL A	4	4	3	1	0	0	0.802549181	0	0.078900827	0.008548851	0	0.110001142	56%
INITIAL A	7	5	3	1	1	1	0.121571349	0	0.005150527	0.396882982	0.015151073	0.46124407	38%
INITIAL A	9	7	3	1	1	0	0.438814828	0	0.127782022	0.180280098	0.000820379	0.252302673	49%
AMOSA	10	16	3	1	0	0	0.244797204	0	0.015581003	0.1609572	0	0.578664594	34%
AMOSA	26	18	3	1	1	0	0.40459782	0	0.053527904	0.227014822	0.133085951	0.181773504	35%
AMOSA	39	21	3	1	1	0	0.331850936	0	0.021482897	0.244686871	0.074513852	0.327465445	44%

Appendix F - Strengths, Weaknesses, Opportunities and Threats of the FTEMT

A four-sector diagram summarising the strengths, weaknesses, opportunities and threats of the FTEMT is provided in Figure F1.

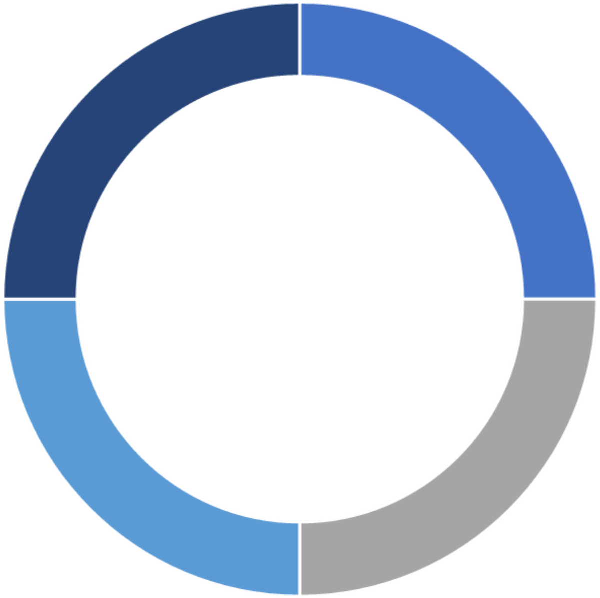
Figure F1 Four-sector diagram of the strengths, weaknesses, opportunities and threats of the FTEMT

Strengths:

- Reduces burden on decision makers
- Does what humans cannot do by considering the full scale of the problem
- Difficult to manipulate the outcomes to suit decision makers' agenda
- Entire decision space is explored, but reduced for decision making purposes
- Trade-offs between solutions are clearly exposed
- Addresses the complexities in developing freight energy management strategies
- High level of stakeholder involvement

Opportunities:

- Improved model formulation in the case study from a transportation planning perspective
- Improved model formulation in the case study from an operations research perspective
- Real-world application of the problem



Weaknesses:

- Simplification of the real-world problem

Threats:

- High volume of data required